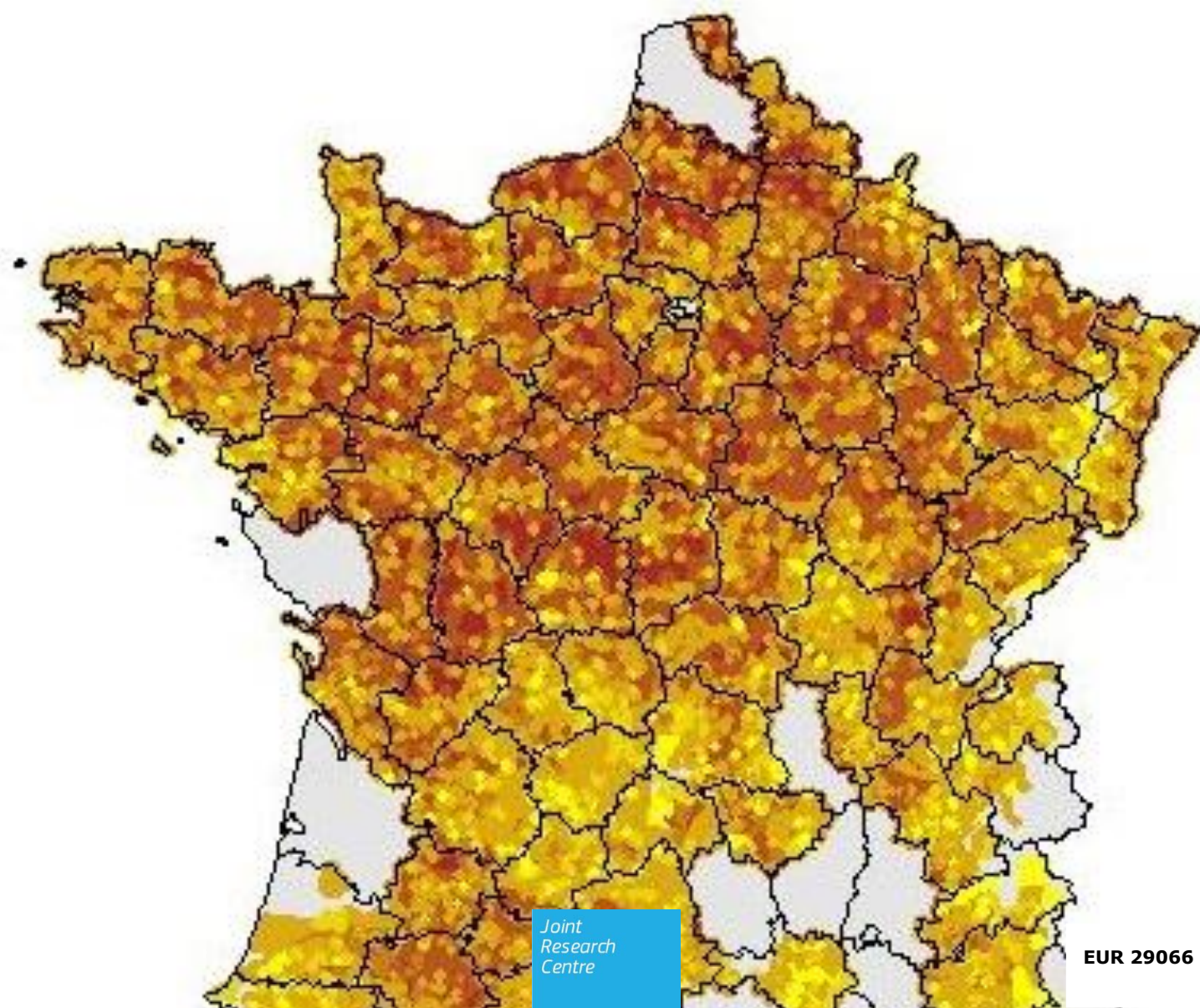


JRC TECHNICAL REPORTS

LAND AREA PREDICTION MODEL (LAPM) Accuracy Assessment

Leip, A., Koeble, R. & Rotllan-Puig, X.

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Authors

Adrian Leip, Renate Koeble & Xavier Rotllan-Puig

Abstract

This document shows the methodology used to assess the accuracy of the new Land Area Prediction Model (LAPM), as well as the results of the assessment.

LAPM aims at predicting land-use areas within each fine-scale Homogenous Spatial Units (HSU). It has been evaluated its accuracy comparing its predictions with LPIS data aggregated to HSU level for France and the Netherlands.

1 Introduction

The first step in the spatial disaggregation of CAPRI regional data and the calculation of agri-environmental indicators at high spatial resolution is the provision of good a priori crop shares for each spatial unit. CAPRI so far uses an agricultural land use map developed in the CAPRI-DynaSpat project (Kempen, 2013; Kempen et al., 2005; Leip et al., 2008) which is based on statistical information collected around the year 2000. The JRC started working on an updated and improved land use share map on the basis of more recent data (2008-2010) and by means of a different approach, the Land Use Disaggregation Model (LUDM; Lamboni et al., 2016).

LUDM results were compared with land use observations at high resolution for France, using data from the LPIS data base (Cantelaube and Carles, 2015). This gave confidence in the performance of the model for the frequent crops, while the model still had some quality deficiencies in predicting non-frequent land uses (Lamboni et al., 2016).

In order to improve the a priori land-use map generated by LUDM, a new completely revised version of the model has been developed. The Land Area Prediction Model (LAPM) aims at predicting land-use areas within each fine-scale Homogenous Spatial Units (HSU), a grid cell of 1 km x 1 km, or a collection of these grid cells having similar properties (Leip et al., 2011). To achieve this goal, LAPM combines point-based observations of land-use from the LUCAS survey (EC, 2003a) with environmental (climate, soil, and land cover classes) and topographical information (relief), by means of multinomial logistic regressions and an iterative approach to select the optimal number of LUCAS points to train the model. In a last step, LAPM also uses available statistical data from the Farm Structure Survey (FSS; EC, 2003b), aggregated at either NUTS3 or 10Km grid level, in order to constrain and refine its predictions. One LAPM model is built for each NUTS2 region and for each of a set of (aggregated) Corine classes in EU-28 plus Norway.

Similarly to the accuracy assessment made to LUDM, here we have evaluated the new LAPM's accuracy for France and the Netherlands (FR and NL, respectively, in this document) using LPIS data aggregated to HSU level. To this aim, we have focussed on those regions (NUTS3 or NUTS2) and land uses where LPIS and FSS have the same crop areas $\pm 10\%$.

The objective of this document is to show the result of the "validation" of the model's result with available LPIS data. The document does not explain in detail the LAP Model and the processing of input data, such as for example the derivation of the FSS2010 data at 10 km grid level, which have been obtained using a dedicated 'gap-filling' model. These models will be described in dedicated separate documents.

Instead, this document describes the methodology used to assess such new model's accuracy, as well as the results of the assessment. Finally, we point out some remarks and conclusions.

2 Methods

2.1 Well-Prediction Indicator (WPI)

With the aim of assessing the accuracy of LAPM predictions, first we have calculated an indicator (Well-Prediction Indicator, WPI) of how the model adequately or badly makes predictions in a qualitative sense (i.e. it makes predictions where there are observations of the crop or it does not make predictions where there are no observations of that crop). This can give a first indication of model performance in the sense of its spatial distribution. WPI is based on the F-measure (Formula 1), which is the harmonic mean between the precision and recall or sensitivity. The precision (P) is the ratio of predictions that have been correctly predicted to the total number of predictions of a certain land use. The recall (R) for that land use is the ration of the number of correct predictions to the total number of observations of the land use. We have calculated WPI for each region (n2) and for those land uses (l) that can be easily delimited in both LAPM predictions and LPIS data set. Table 1 contains all land uses (crops) abbreviations used along this document. Notice that OLIVGR, LMAIZ and VINY come from the addition of OLIV and TABO, MAIZ and MAIF, and TAGR and TWIN, respectively, while the other are direct categories both in LAPM and in LPIS.

$$WPI_{l,n2} = 2 \times \frac{P_{l,n2} \times R_{l,n2}}{P_{l,n2} + R_{l,n2}} \quad , \quad (1)$$

Table 1. Crop abbreviations used in this assessment. Marked with 1 if it is used for France and with 2 for the Netherlands.

APPLOFRU ²	apple and other fruit trees	PARI ¹	rice
BARL ^{1, 2}	barley	POTA ²	potatoes
FLOW ²	flowers	RAPEVSET ¹	rapeseed
GRAI ²	intensive grasslands	RYEM ²	rye
LMAIZ ^{1, 2}	maize	SUGB ²	sugar beet
NURS ²	nurseries	SUNF ^{1, 2}	sunflower
OATS ²	oats	SWHE ^{1, 2}	soft wheat
OCER ²	other cereals	TOMAOVEG ²	tomatoes and other vegetables
OFAR ²	other forages	VINY ¹	vineyard
OLIVGR ¹	olives		

2.2 Scatter plots

Secondly, we have produced scatter plots of LAPM predictions versus LPIS data (observations), at HSU level. In addition, in order to check whether the finer FSS data used as input in LAPM improves its results, we have produced scatter plots before any constraint, as well as for predictions constrained using aggregated FSS data at10Km-grid and NUTS3 level.

2.3 Unweighted Error E

Thirdly, as a quantitative indicator, we have calculated LAPM prediction errors (called unweighted errors in this document) as follows:

$$E_{l,h} = \sqrt{(a_{h,l}^O - a_{h,l}^P)^2} \quad , \quad (2)$$

where $E_{l,h}$ is the error term of a given land-use (l) and HSU (h), in ha, $a_{h,l}^O$ is the observed land-use area and $a_{h,l}^P$ is the predicted area.

Additionally, taking into account the variability in the HSUs areas, we have also calculated relative prediction errors (dimensionless) as follows:

$$E_{l,h} = \frac{\sqrt{(a_{h,l}^O - a_{h,l}^P)^2}}{a_h} \quad (3)$$

With both unweighted and relative error terms calculated for each HSU in France and the Netherlands, we have generated some statistics (i.e. mean, median, 3rd quartile, percentile-90 and maximum). However, to avoid the effect of the outliers, which affect both mean and maximum values, we have focussed on the median and percentiles of these errors for the analysis.

In addition, in most of the regions, there are many errors set to zero. This is in particular true for un-frequent crops, which are neither observed nor predicted for a large number of spatial units. Such significant amount of zeros could affect median and percentiles. Thus, although they mean good performance of the model, we have computed statistics from both unweighted and relative prediction errors also removing these zeros. As the latter (without zeros) is a more conservative way to present the results, we will only show these values in the Results section below.

2.4 Maps

Finally, to check if any spatial pattern in the prediction errors can be observed, some maps are provided. Additionally, for France, we plot together the errors produced by LUDM and the errors produced by LAPM, so that we can have a visual indication of the improvements provided by the new modelling approach. It has to be kept in mind, however, that the data used to refine LUDM predictions is at a coarser scale than the one used in LAPM (FSS aggregated at NUTS3 and 10Km, respectively). Therefore, any conclusions have to be taken with caution.

3 Results and discussion

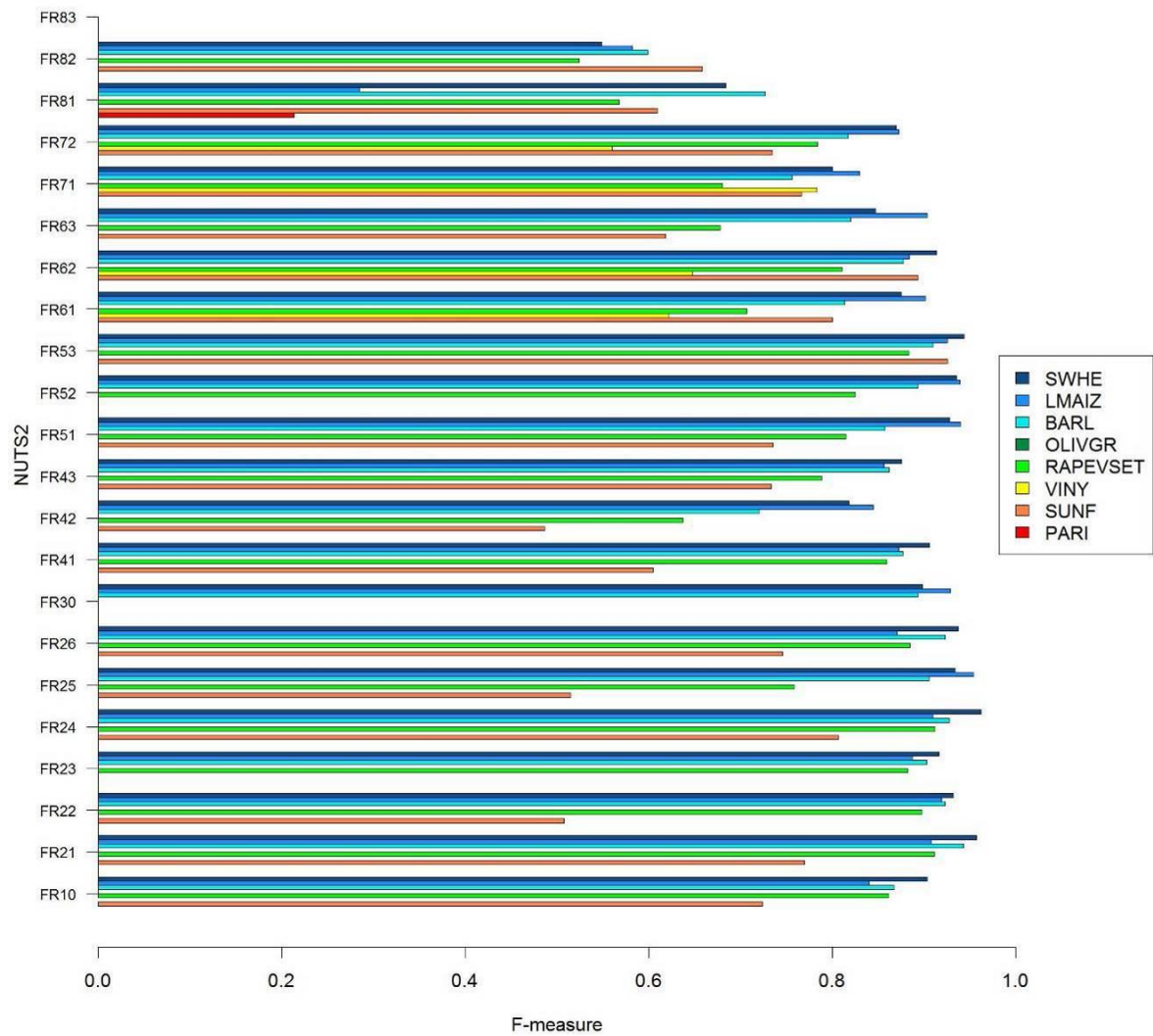
3.1 Well-Prediction Indicator (WPI)

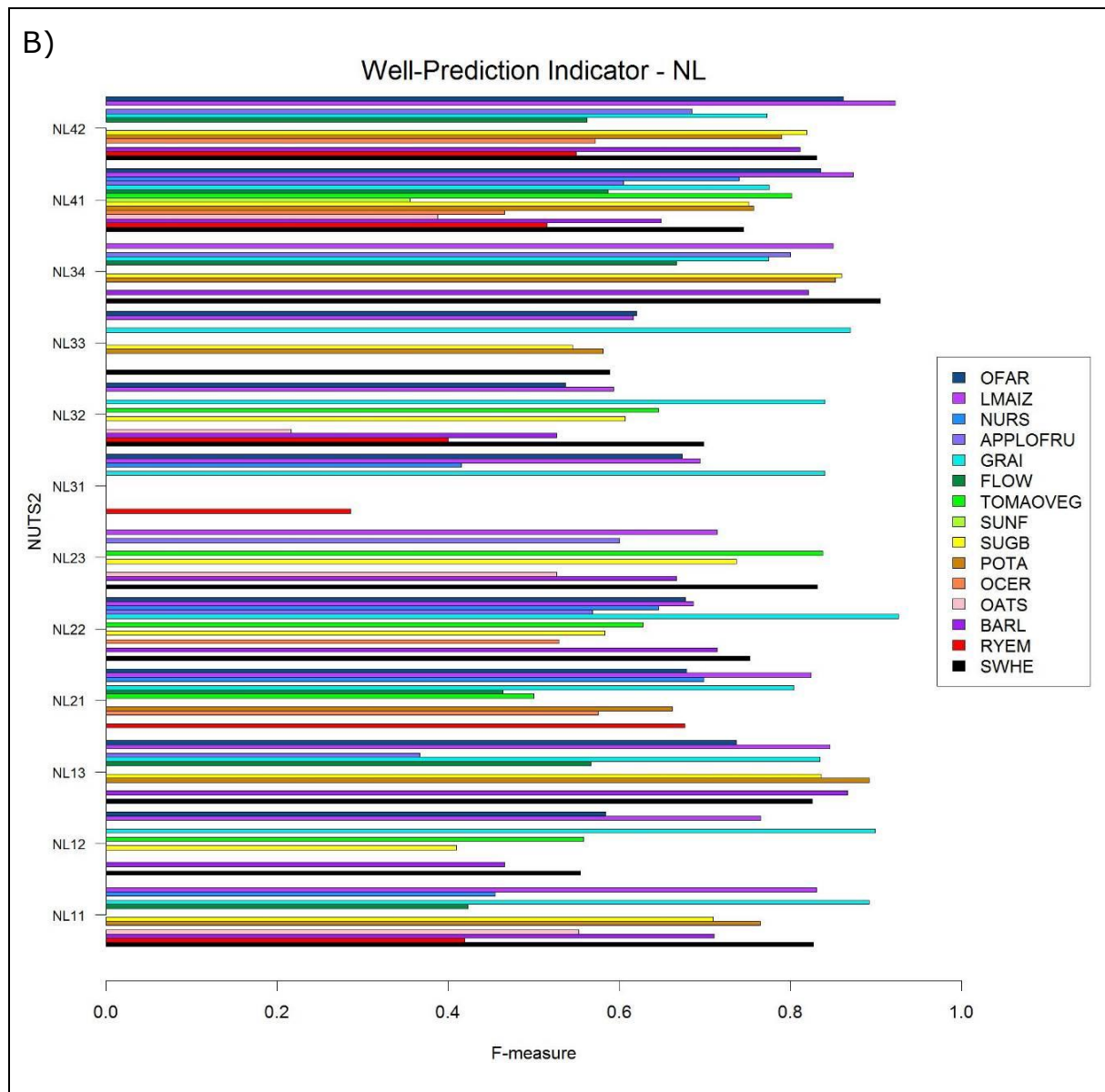
Figures 1A and 1B show bar-plots of the WPI for France and the Netherlands respectively. The results are also separated per NUTS2 and crop. Most of the F-measure values for France are over 0.75, what gives a first indication of a general good performance of LAPM. However, FR81 and FR82 have all crops around 0.5-0.7. By crops, SWHE, LMAIZ and BARL are the ones with highest results, while PARI (although it has only one result for FR81) shows the poorest and SUNF and VINY have also values around 0.5-0.6 in some regions. On the other hand, the Netherlands shows more heterogeneous performance, particularly from the point of view of the crops. GRAI, LMAIZ and OFAR show better results, with values around 0.75 or more in most of the regions, while OATS and RYEM show not very good values of this indicator in some regions (e.g. NL31 and NL32).

Figure 1. Well-Prediction Indicator per NUTS2 and crops. F-measure equals to 0 stands for absolute bad prediction, while equals to 1 stands for completely well predicted

A)

Well-Prediction Indicator - FR





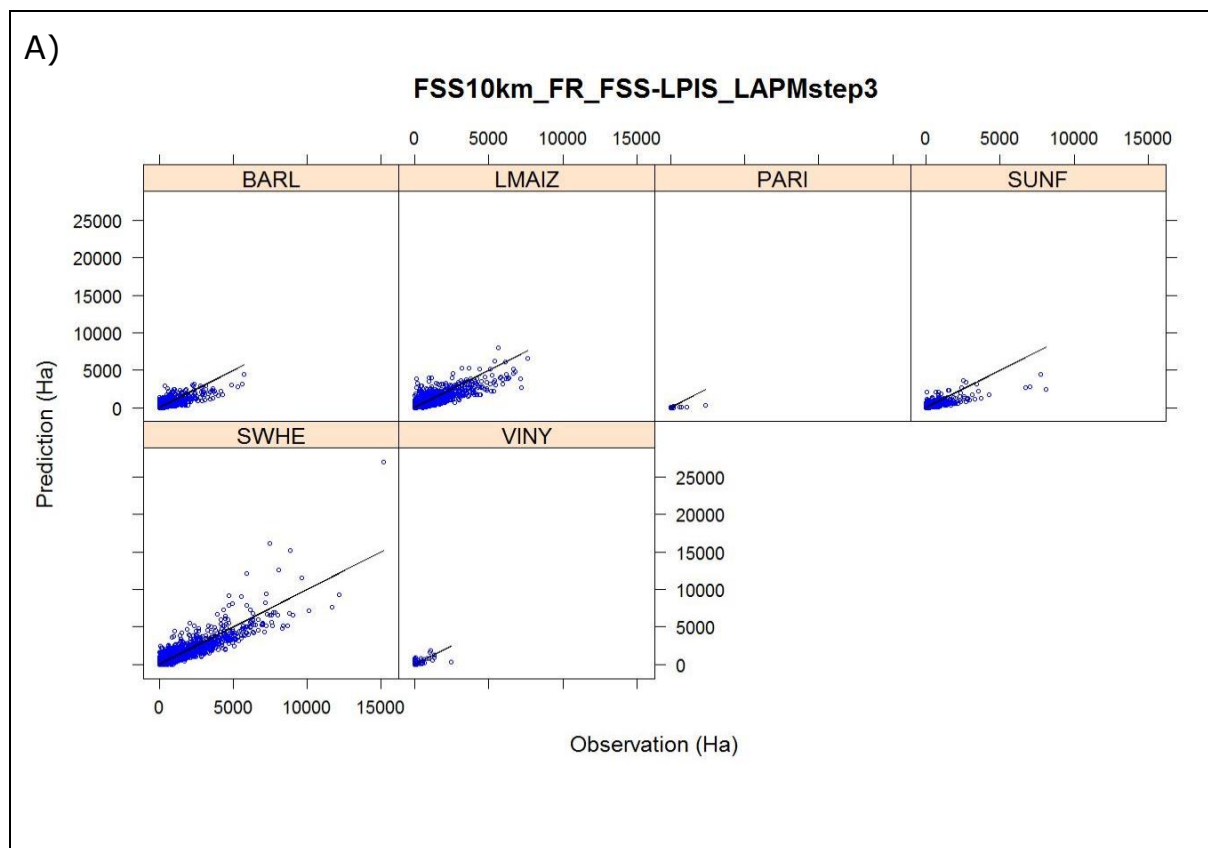
3.2 Scatter plots

The scatter plots in Figure 2 show predictions versus observations for France at HSU level and for the crops tested. Fig. 2A presents results of LAPM predictions before applying any constraining to FSS data, either at NUTS3 level or at 10Km-grid. It shows how such predictions are already quite good even just after LAPM Steps 1 to 3, which is already an important improvement with regard to LUDM. Note that area-information is used before LAPM Step 4, so the correlation between observations and predictions rather than the slope indicates the quality of the prediction.

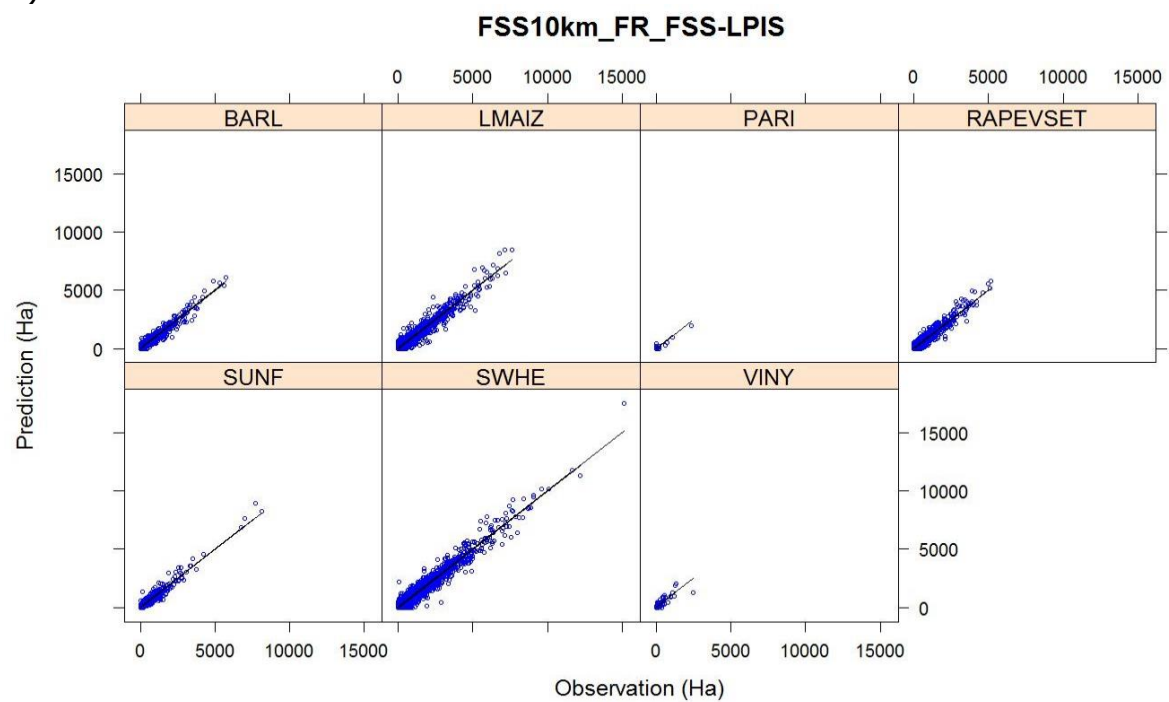
Fig. 2B show LAPM predictions after using FSS data aggregated at 10Km-grid to constrain them. Finally, Fig. 2C shows predictions obtained with LUDM constrained to FSS data at NUTS3 level, also against LPIS observations. In these three charts, we can see how LAPM using FSS data aggregated at a finer scale (Fig. 1B) preforms better than both LUDM and itself before constraining to FSS data.

LAPM model predicts generally well for France and for all crops; also for those less-frequent crops that LUDM was revealed as more problematic (e.g. PARI and VINY).

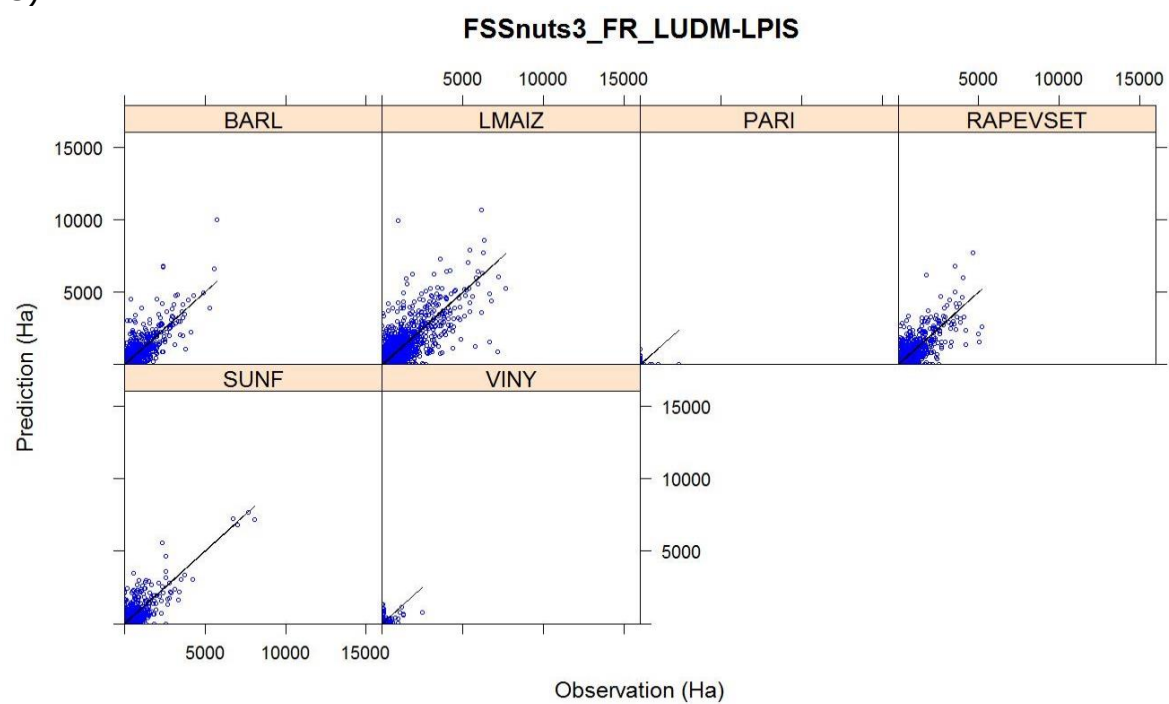
Figure 2. Blue spots stand for predictions (LAPM or LUDM) versus observations (LPIS) for France, while black line represents observations versus observations. 2A presents results before constraining predictions to FSS, while 2B presents the results after using FSS data aggregated at 10Km-grid (i.e. final predictions). 1C presents the results obtained with LUDM



B)

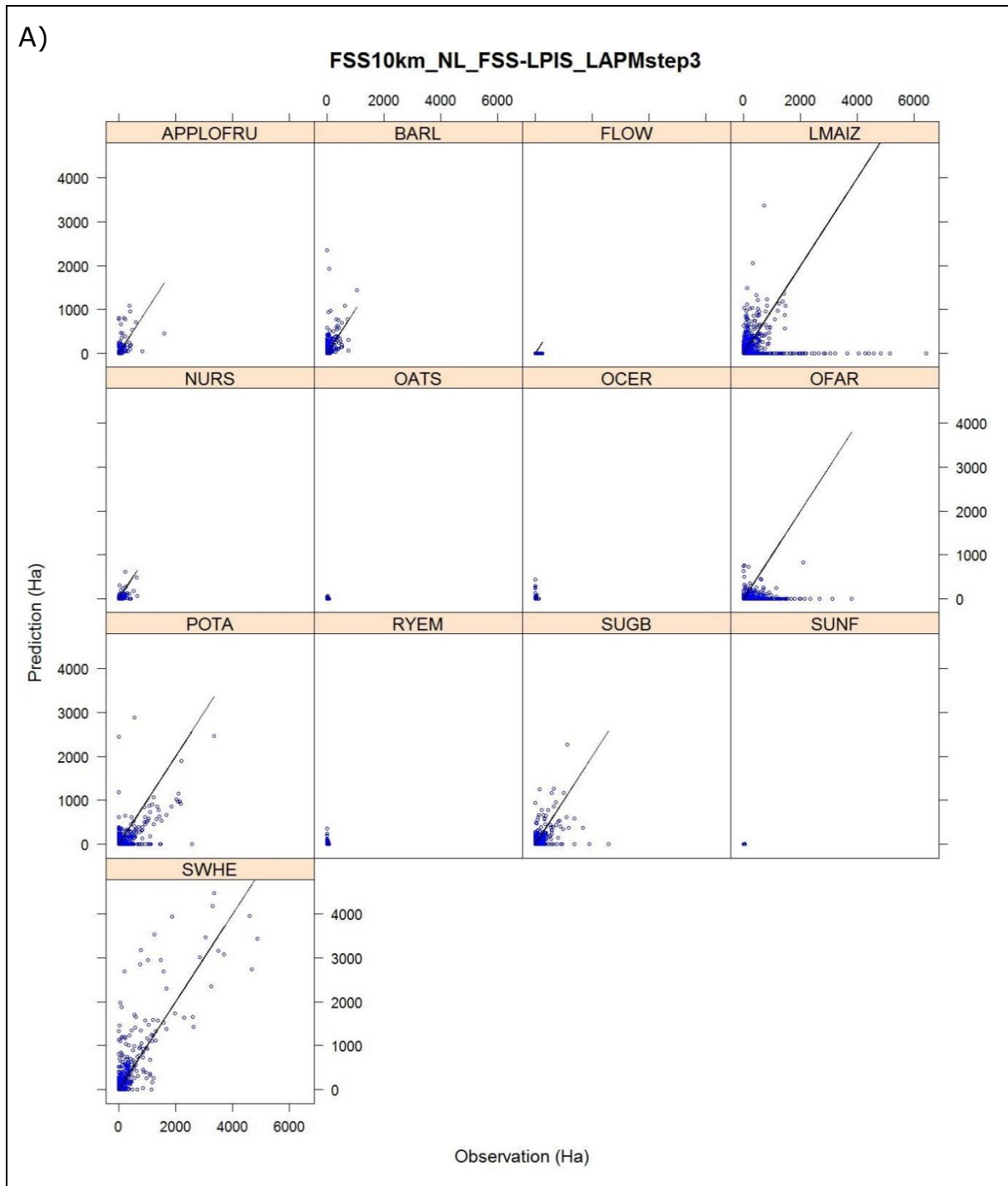


C)

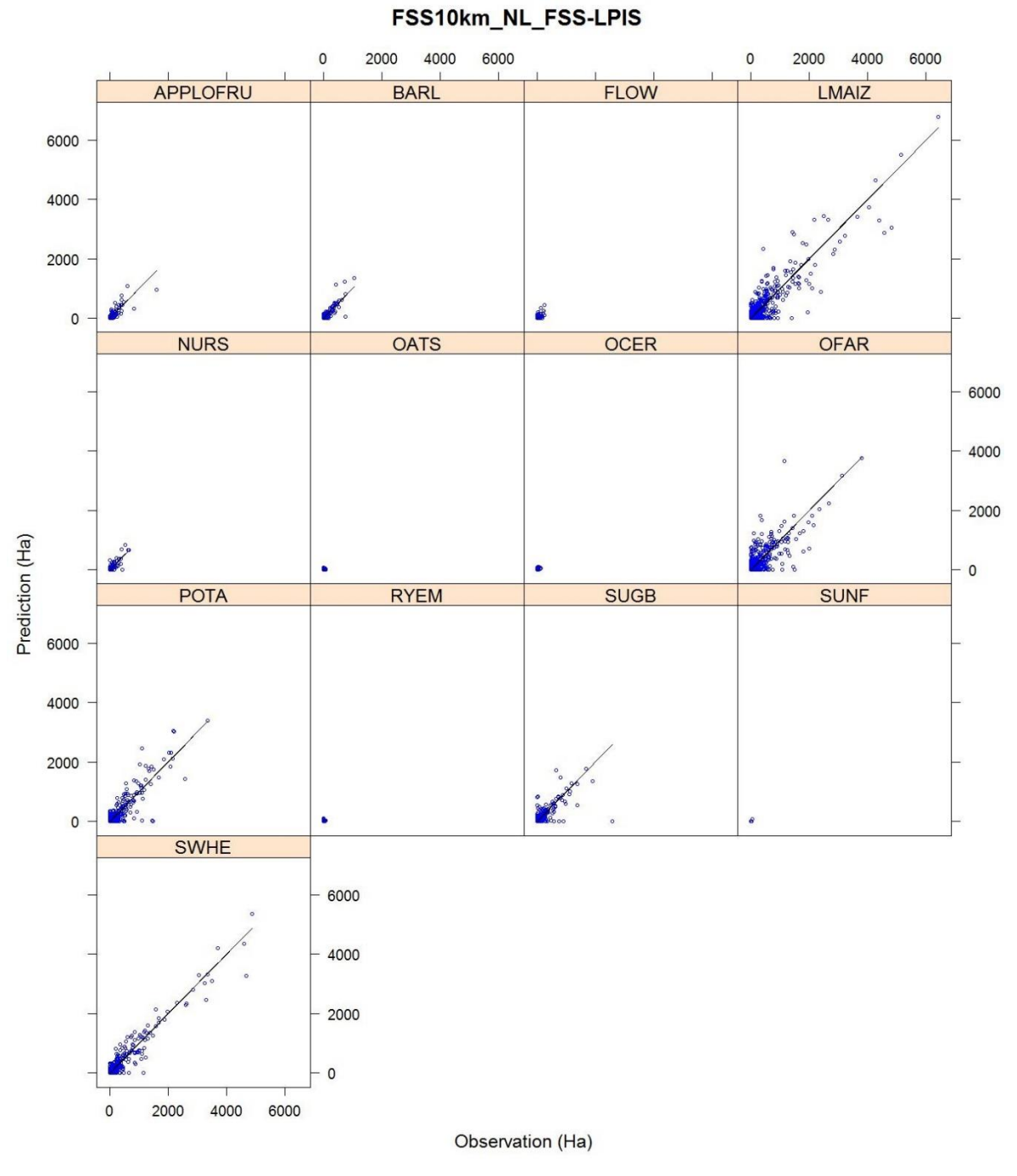


Equally, Fig. 2A and Fig. 2B show the scatter-plots LAPM predictions versus LPIS observations for the Netherlands. LAPM's performance is also quite good for this country, especially after constraining to FSS data at a fine scale.

Figure 3. Blue spots stand for predictions (LAPM or LUDM) versus observations (LPIS) for the Netherlands, while black line represents observations versus observations. 3A presents results before constraining predictions to FSS, while 3B presents the results after using FSS data aggregated at 10Km-grid (i.e. final predictions)



B)



3.3 Unweighted Error E

Tables 2 show for France values of the statistics computed from both unweighted (absolute) and relative prediction error terms, and keeping only prediction errors not equal to zero. The table shows only the maximum error term calculated in the NUTS2 region with the worst performance of the crop.

More detail is given in Figure 4, showing the accuracy of LAPM predictions in France by NUTS2 region and crops. The figure shows separately median, 3rd quartile, percentile-90

and maximum of the error terms. Note that we have fixed the scale of the plots to percentile-90 values. Therefore, biggest maximums are out of these limits and thus not shown.

For all crops, the 3rd quartile (i.e. 75% of the error terms are below that value) is lower than 200Ha (Table 2A). The maximum error for outliers is mostly above 1100Ha.

However, the relative errors (Table 2B), are probably more explanatory. Also focused on the 3rd quartile, most crops have got relative errors to HSU area equal or less than 0.20. This would mean that the errors of 75% of HSUs are less than a 20% of their area. Only PARI and RAPEVSET have slightly larger relative errors with a 3rd quartile of 0.25 and 0.35, respectively.

For most regions, largest errors are found for SWHE or LMAIZ.

Table 2. Maximum values of statistics derived from unweighted (2A; results in Ha) and relative to HSU area (2B) errors for France and the NUTS2 where the maximum is given, after removing zeros

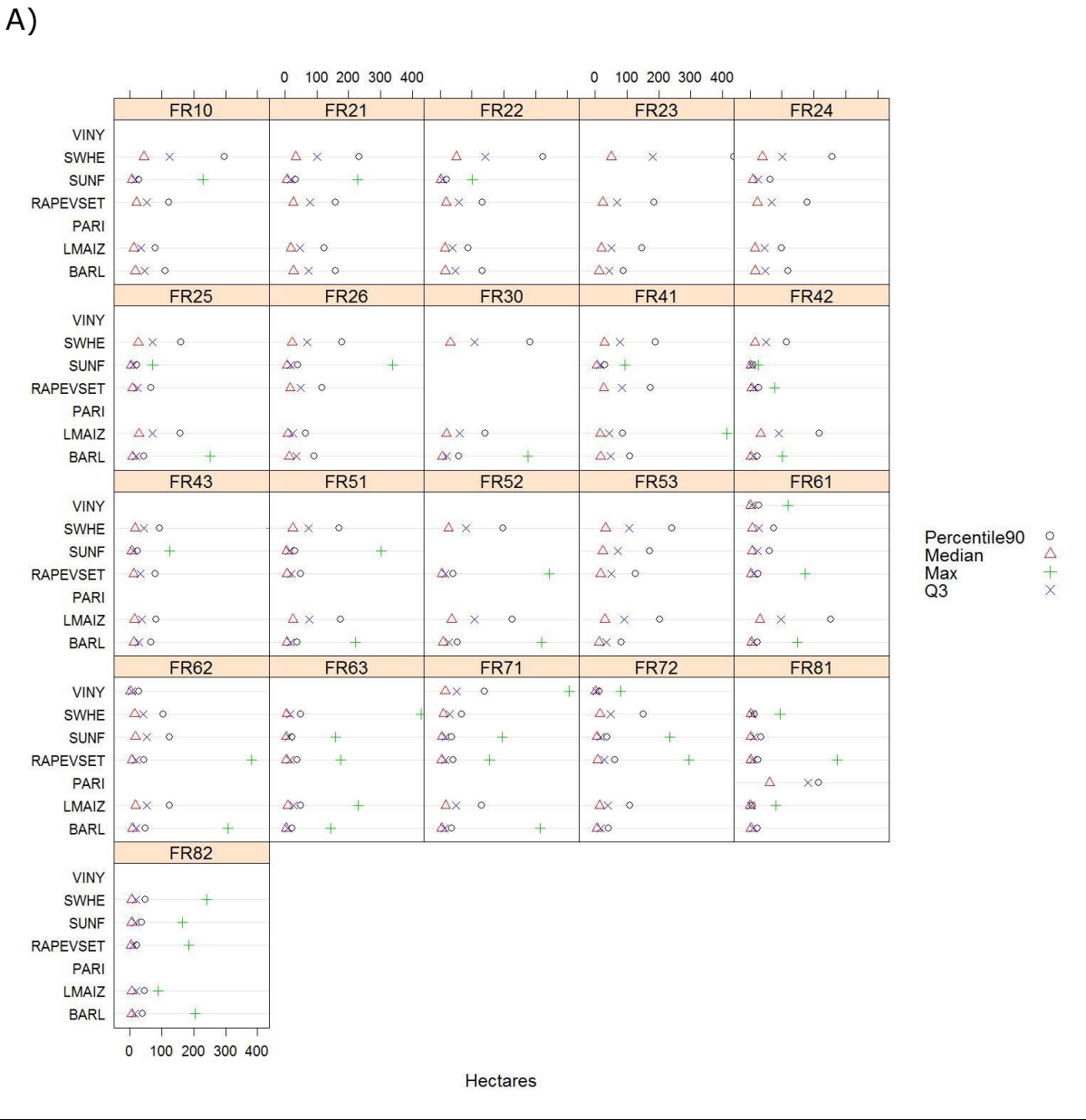
A)

	Crop	Max_P90	Max_Median	Max_Q3	Max_Max	in_NUTS2
1	BARL	158.98	27.00	73.675	1120.7	FR21
2	LMAIZ	254.25	36.50	109.000	2126.7	FR61
3	PARI	214.56	62.20	181.825	458.6	FR81
4	RAPEVSET	184.57	27.20	84.250	1287.9	FR22
5	SUNF	171.74	23.95	72.300	1237.3	FR62
6	SWHE	436.54	51.30	181.200	2442.9	FR10
7	VINY	140.26	16.95	52.450	1246.5	FR62

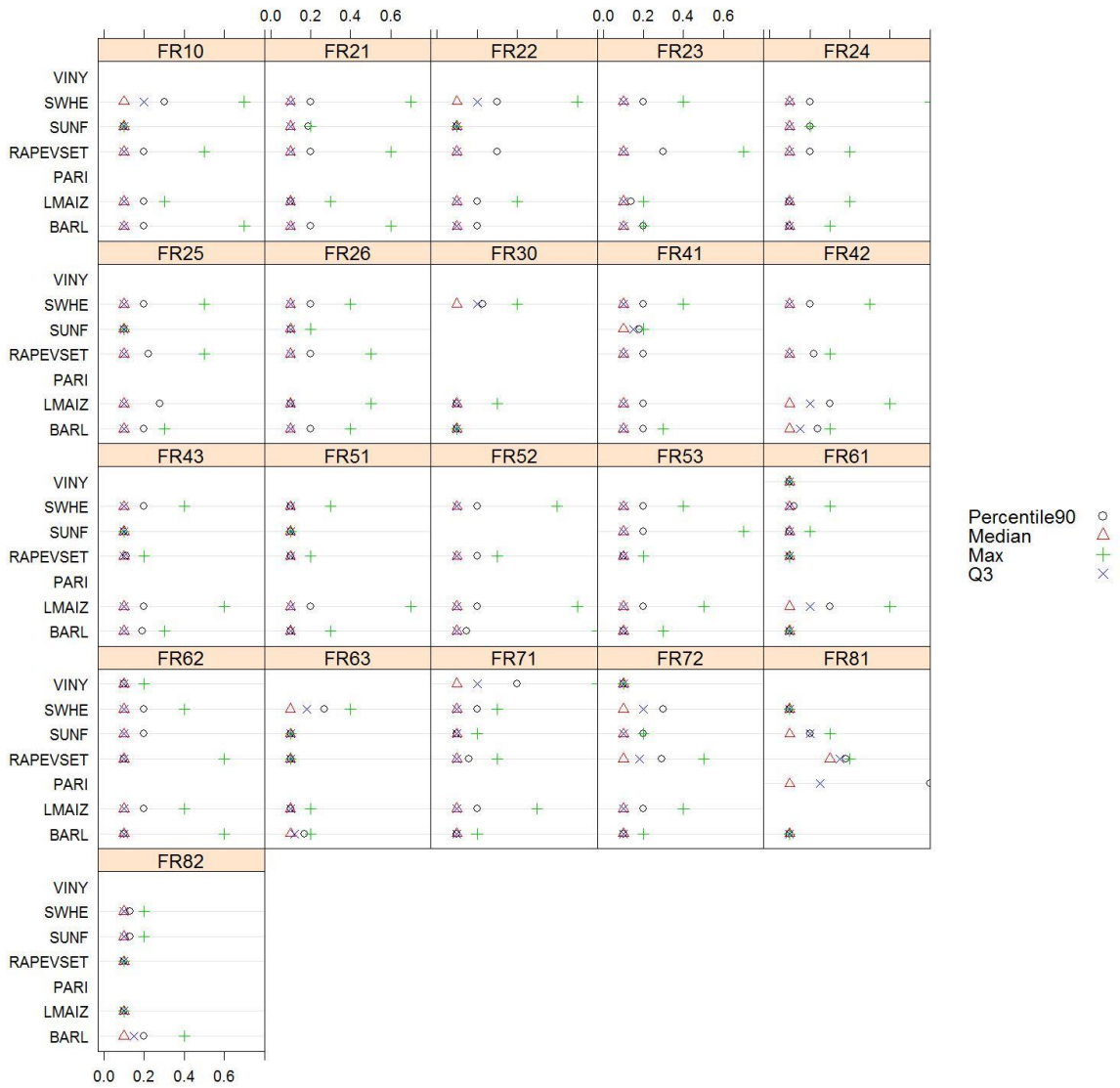
B)

	Crop	Max_P90	Max_Median	Max_Q3	Max_Max	in_NUTS2
1	BARL	0.24	0.1	0.15	0.9	FR22
2	LMAIZ	0.30	0.1	0.20	1.0	FR25
3	PARI	0.80	0.1	0.25	1.0	FR81
4	RAPEVSET	0.38	0.3	0.35	0.9	several
5	SUNF	0.20	0.1	0.20	0.9	FR62
6	SWHE	0.30	0.1	0.20	0.9	FR72
7	VINY	0.40	0.1	0.20	0.8	FR71

Figure 4. Median, 3rd quartile, percentile-90 and maximum values derived from unweighted (4A; results in Ha) and relative to HSU area (4B) errors for France and separated by NUTS2, after removing zeros



B)



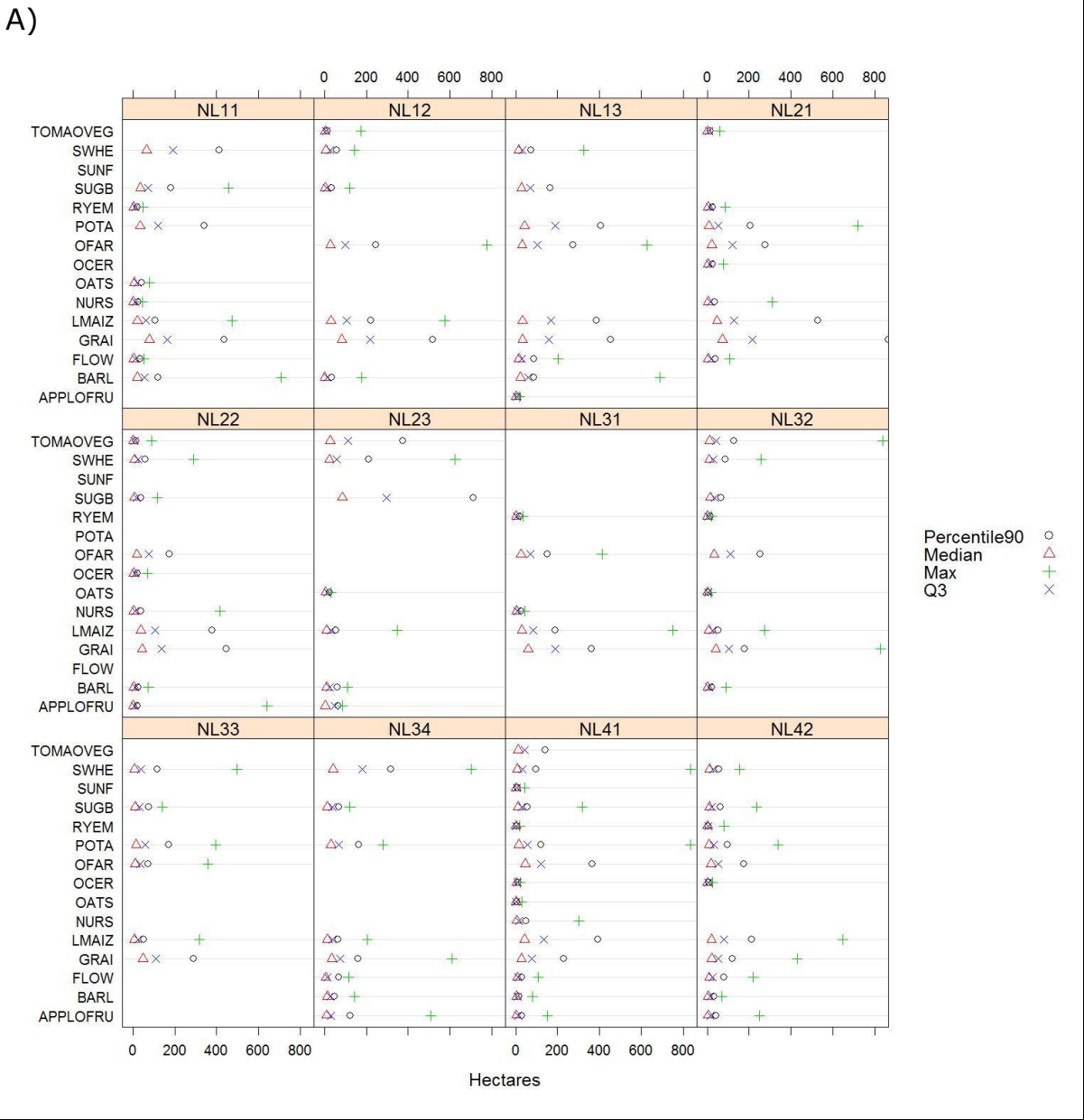
Predictions for the Netherlands show absolute errors (Table 3A) proportionally similar to the ones of France for most of the crops. OATS, NURS, RYEM and OCER show values below 20Ha, while SUGB and GRAI show results above 200Ha. In relative terms (Table 3B), FLOW and GRAI are the worst, with 0.48 and 0.30, respectively, and APPLOFRU and OATS the best ones with 0.1. Splitting by regions, the results are more variable, although in relative terms (Fig. 5B) all the crops in all NUTS2 have 3rd percentiles clearly below 0.4, except FLOW in NL13 with 0.48.

Table 3. Maximum values of statistics derived from unweighted (3A; results in Ha) and relative to HSU area (3B) errors for the Netherlands and the NUTS2 where the maximum is given, after removing zeros

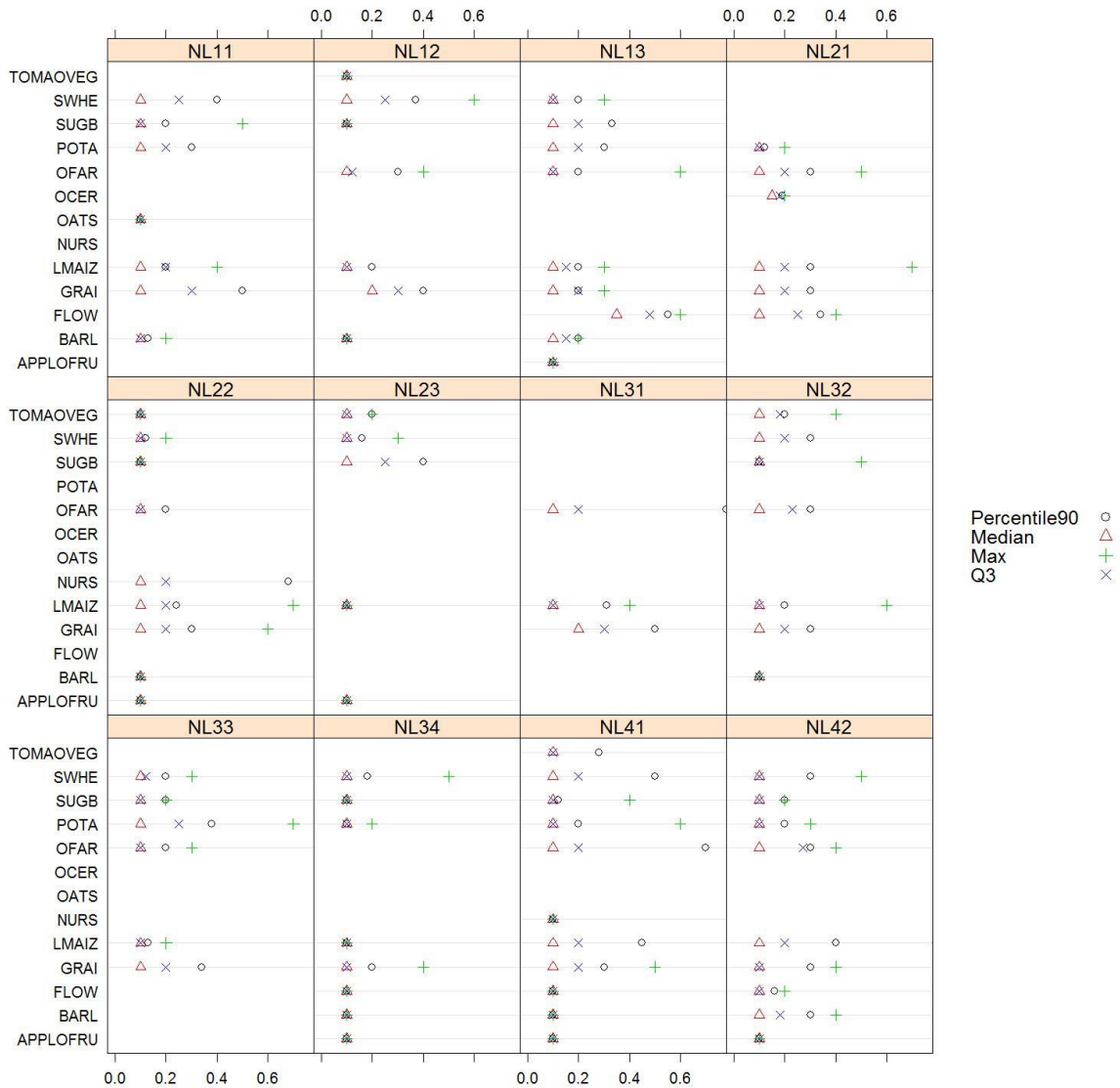
A)						
	Crop	Max_P90	Max_Median	Max_Q3	Max_Max	in_NUTS2
1	APPLOFRU	121.86	10.60	48.250	642.1	NL22
2	BARL	119.10	22.50	60.200	709.2	NL11
3	FLOW	87.72	14.40	27.800	220.8	NL42
4	GRAI	865.50	83.50	217.500	2076.8	NL21
5	LMAIZ	528.94	46.80	169.550	1934.2	NL21
6	NURS	49.68	5.20	14.450	415.0	NL22
7	OATS	41.27	6.10	20.850	79.4	NL11
8	OCER	26.80	4.80	11.900	76.9	NL21
9	OFAR	363.98	46.00	120.700	2526.9	NL32
10	POTA	407.57	41.95	189.375	1479.4	NL13
11	RYEM	23.48	5.00	12.050	87.1	NL21
12	SUGB	711.78	86.60	296.400	2573.1	NL23
13	SUNF	6.69	0.80	3.875	40.6	NL41
14	SWHE	414.04	64.60	192.200	1401.2	NL11
15	TOMAOVEG	375.92	27.30	112.350	1066.2	NL23

B)						
	Crop	Max_P90	Max_Median	Max_Q3	Max_Max	in_NUTS2
1	APPLOFRU	0.10	0.10	0.10	0.1	several
2	BARL	0.30	0.10	0.18	0.4	NL42
3	FLOW	0.55	0.35	0.48	0.6	NL13
4	GRAI	0.50	0.20	0.30	1.0	several
5	LMAIZ	0.45	0.10	0.20	0.9	NL41
6	NURS	0.68	0.10	0.20	1.0	NL22
7	OATS	0.10	0.10	0.10	0.1	NL11
8	OCER	0.19	0.15	0.18	0.2	NL21
9	OFAR	0.78	0.10	0.27	1.0	several
10	POTA	0.38	0.10	0.25	1.0	NL11
11	SUGB	0.40	0.10	0.25	1.0	NL13
12	SWHE	0.50	0.10	0.25	1.0	NL32
13	TOMAOVEG	0.28	0.10	0.18	0.8	NL41

Figure 5. Median, 3rd quartile, percentile-90 and maximum values derived from unweighted (5A; results in Ha) and relative to HSU area (5B) errors for the Netherlands and separated by NUTS2, after removing zeros



B)

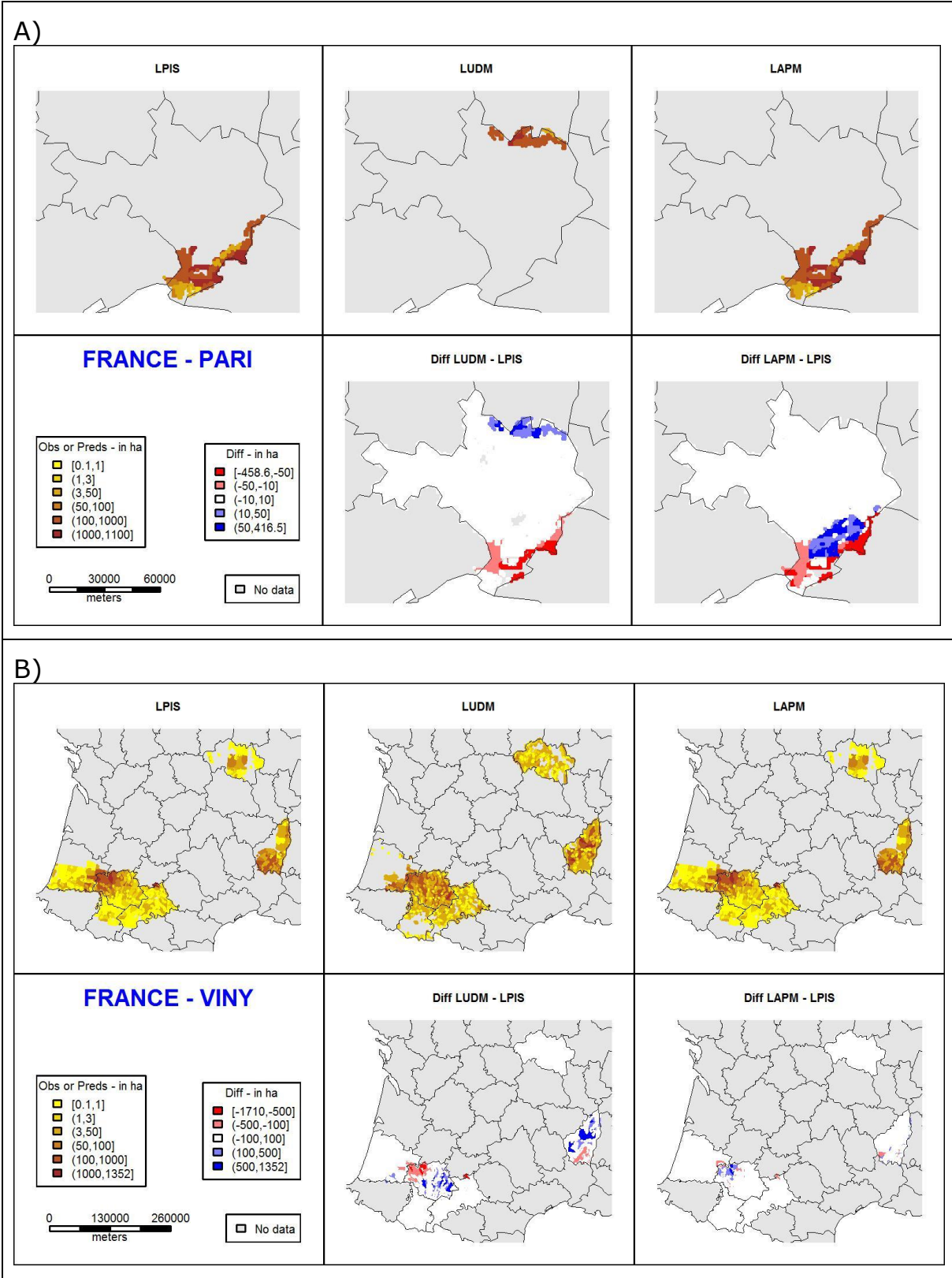


3.4 Maps

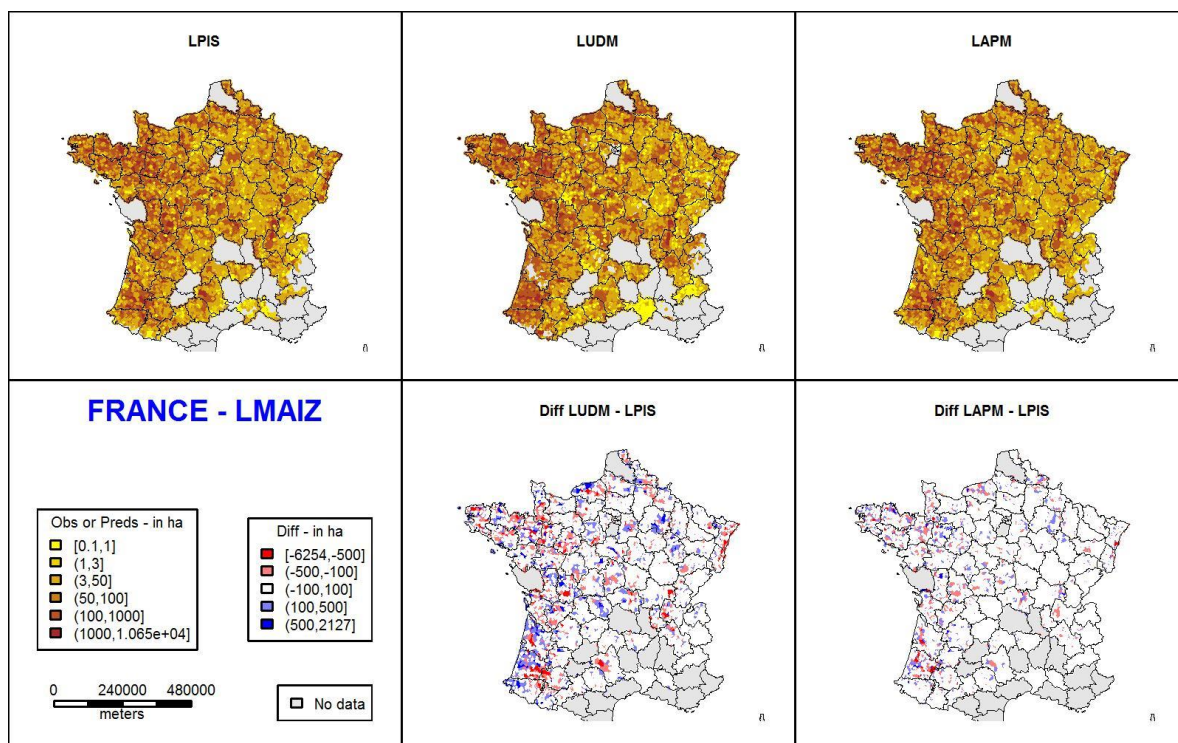
Lastly, we present some maps comparing both French prediction errors of LAPM and LUDM for some of those land-uses that have been shown as more problematic either in the assessments above or in LUDM (i.e. PARI, VINY, LMAIZ and SWHE). In addition, in ANNEX1 and 2 we show maps for the rest of the crops included in this validation for France, as well as for the Netherlands.

For PARI, we can see in Fig. 6A how LAPM, although it still has errors $> \pm 50$ Ha, it performs spatially considerably better than LUDM. On the other hand, Figs. 6B and 6C show how LAPM reduces the quantity of dark red and dark blue spots in relation to LUDM. Finally, regarding SWHE, Fig. 6D also shows good predictions of LAPM. We do not have LUDM predictions because that model does not have SWHE (soft wheat) category.

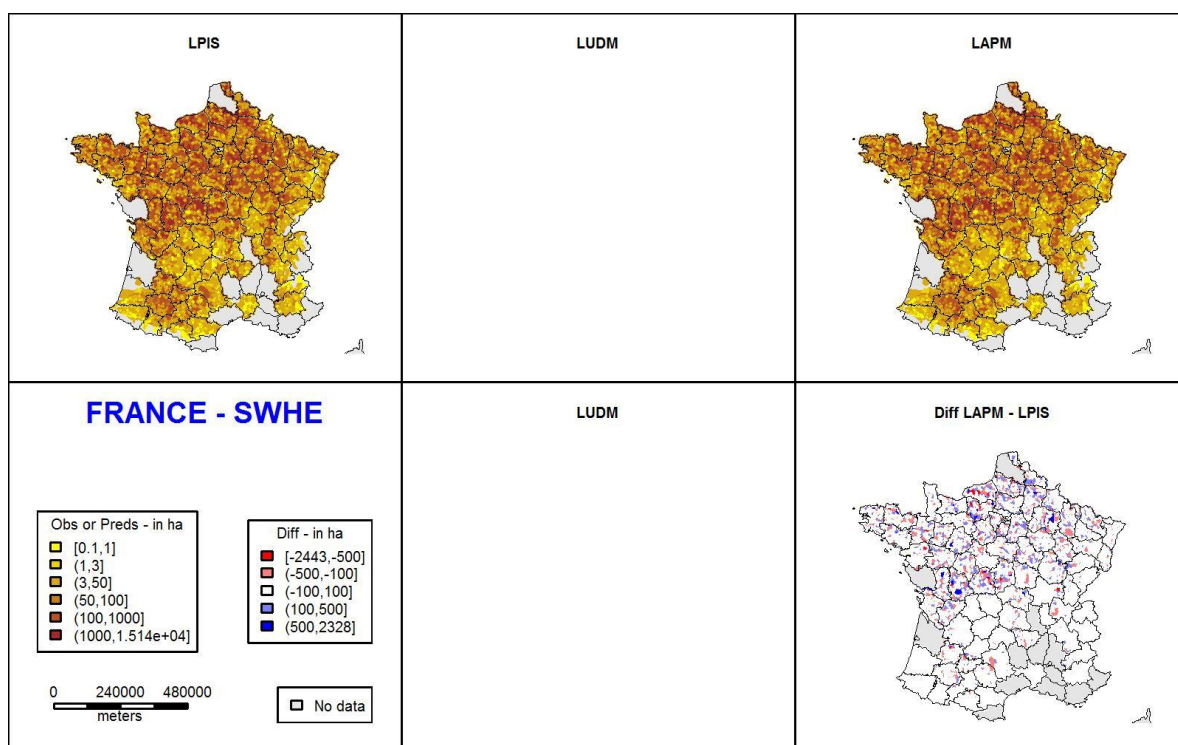
Figure 6. LPIS data aggregated at HSU level, LUDM and LAP predictions for PARI, VINY, LMAIZ and SWHE. Also differences between LPIS and both LUDM and LAP predictions. All values in Ha.



C)



D)



4 Conclusions

In this document we show the comparison of results from the Land Area Prediction Model (LAPM) with LPIS data for France and the Netherlands. We analysed those crops that have comparable categories in both data sets, but we focus especially on those crops/country combinations which showed the worst results, such as PARI or VINY for France.

The predictions of LAPM are generally good for most of the regions (NUTS2) and crops analysed in both countries. In addition, the improvement of the performance of LAPM compared to LUDM has been shown as very important for most of the crops. We observe a higher accuracy for the prediction for France as compared to the Netherlands. Possible reasons for this are the stronger influence of explanatory variables not captured in LAPM (such as infrastructure or distance to the market –cities) or the most homogeneous landscape and environmental conditions in the Netherlands.

The case of PARI needs to be especially under consideration, as it was one of the non-frequent crops poorly predicted by LUDM. Although it has only one region available to assess in France for LAPM, it has shown a notable improvement, particularly from the point of view of the spatial distribution of the predictions.

Unfortunately, LPIS or other 'real' data are not available for all countries. However, efforts will be made and this assessment will be extended to more countries as far as possible, especially to eastern and northern areas of Europe.

References

- Cantelaube, P., Carles, M., 2015. Le registre parcellaire graphique: des données géographiques pour décrire la couverture du sol agricole, in: Cahier Des Techniques de l'INRA, Special Issue GéoExpé. pp. 58–64
- EC, 2003a. The Lucas survey. European statisticians monitor territory, Theme 5: Agriculture and fisheries. Office for Official Publications of the European Communities, Luxembourg
- EC, 2003b. Farm structure 1999/2000 survey. Office for Official Publication of the European Communities, Luxembourg
- Kempen, M., 2013. EU wide analysis of the Common Agricultural Policy using spatially disaggregated data
- Kempen, M., Heckelei, T., Britz, W., 2005. An econometric approach for spatial disaggregation of crop production in the EU. Working paper presented at the EAAE Seminar, Parma, 3-5 February 2005. University of Bonn, Institute for Agricultural policy, market Research and Economic sociology.
- Lamboni, M., Koeble, R., Leip, A., 2016. Multi-scale land-use disaggregation modelling: Concept and application to EU countries. *Environ. Model. Softw.* 82, 183–217. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.04.028>
- Leip, A., Marchi, G., Koeble, R., Kempen, M., Britz, W., Li, C., 2008. Linking an economic model for European agriculture with a mechanistic model to estimate nitrogen and carbon losses from arable soils in Europe. *Biogeosciences* 5, 73–94. doi: <http://dx.doi.org/10.5194/bg-5-73-2008>
- Leip, A., Wattenbach, M., Reuter, H.I., Koeble, R., Balkovic, J., Skalsky, R., Obersteiner, M., 2011. A new data infrastructure for European terrestrial ecosystem modelling - Development of Unified Spatial Characterisation Identifier for Europe (uscie)

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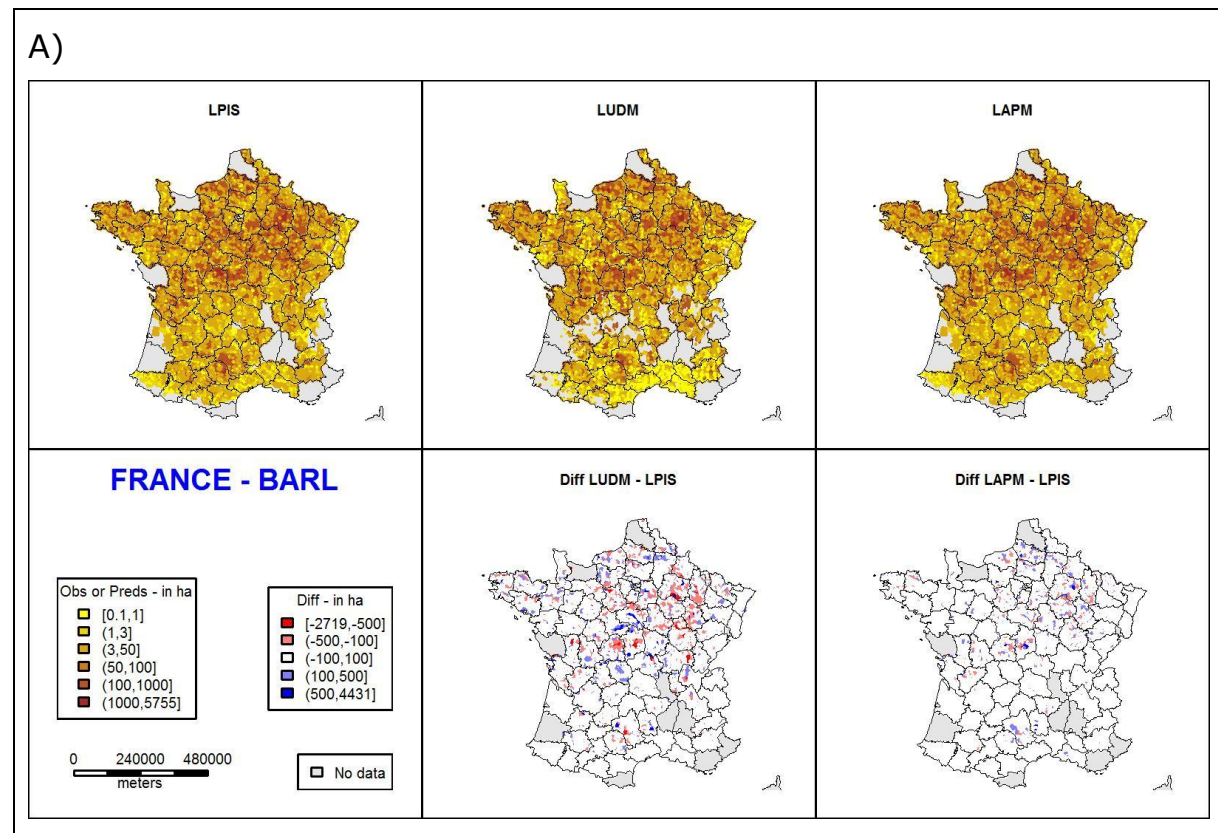
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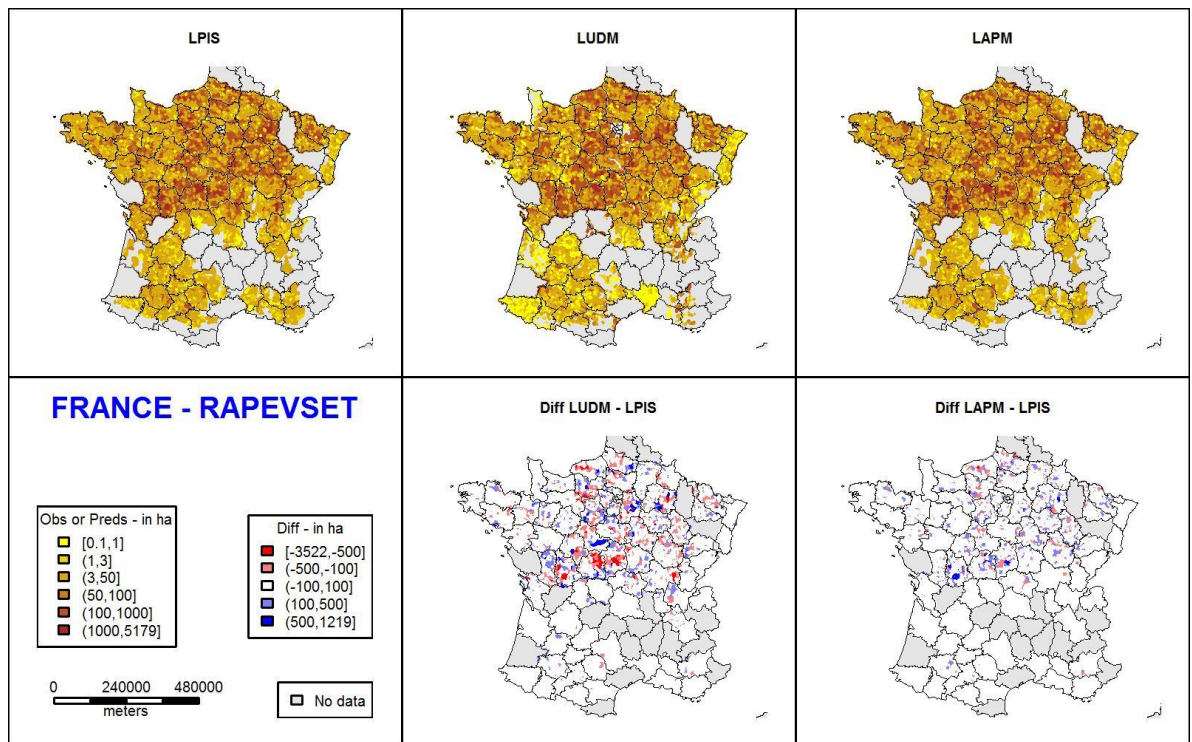
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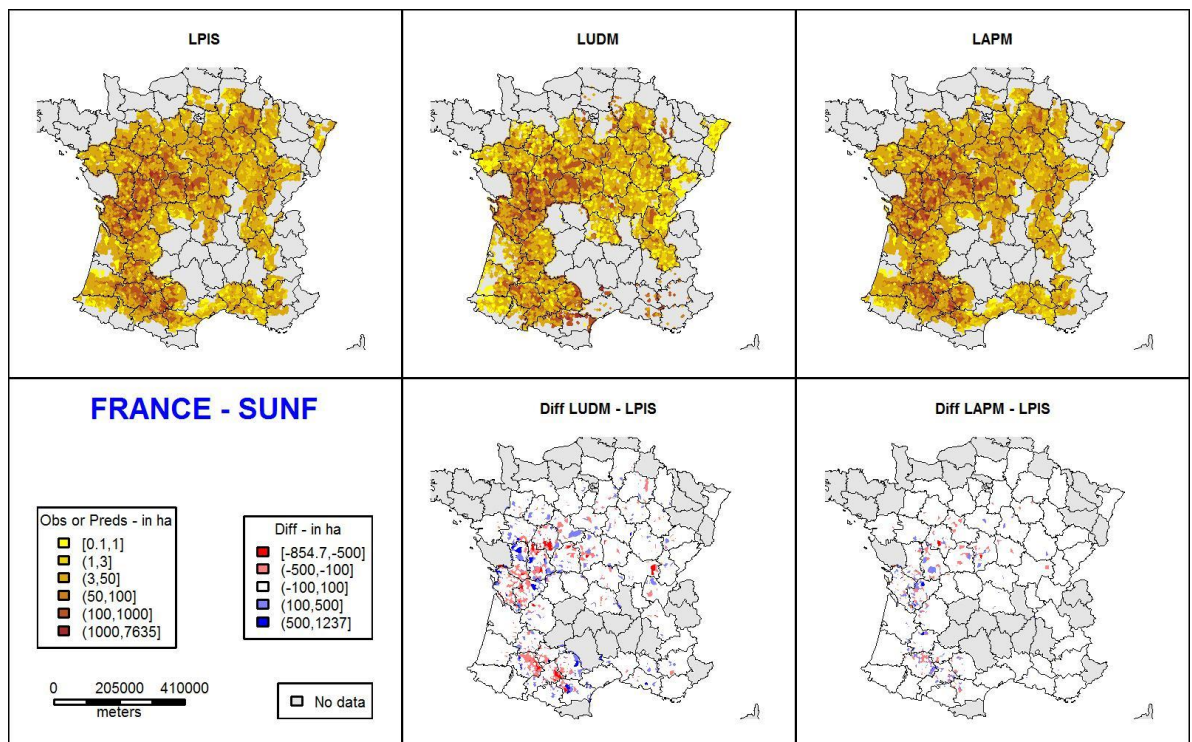
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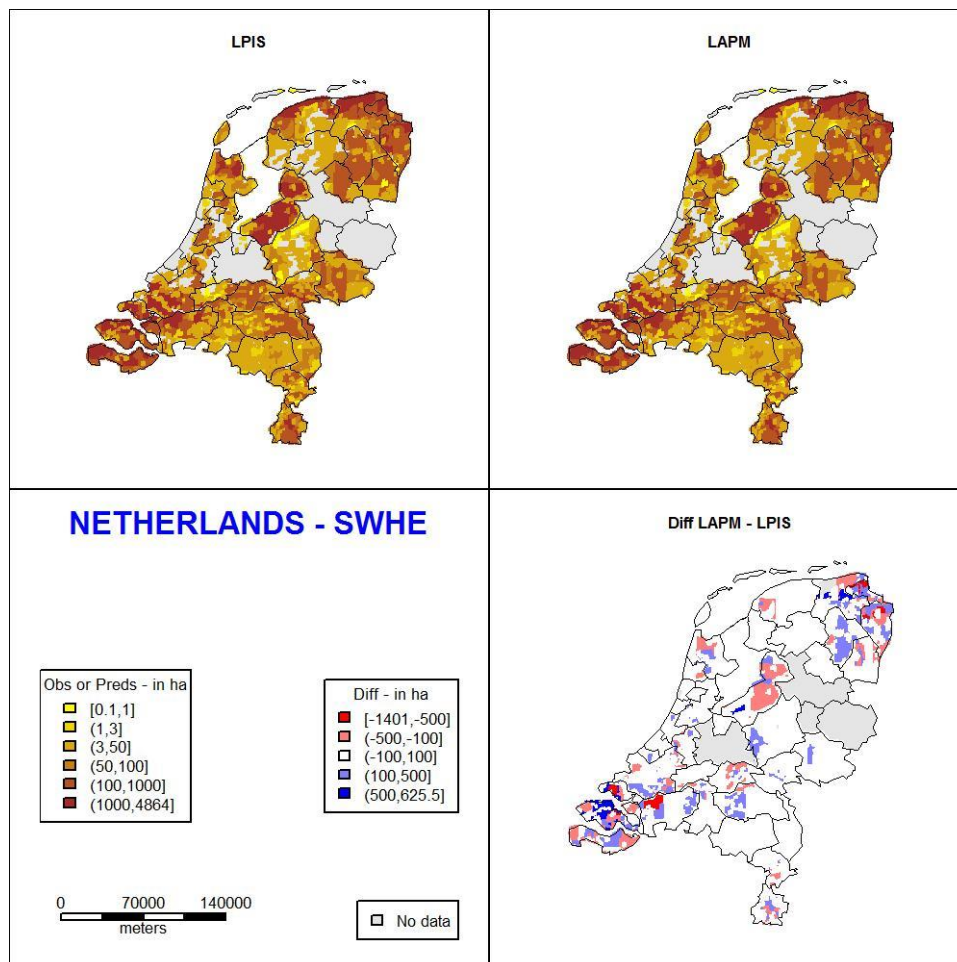


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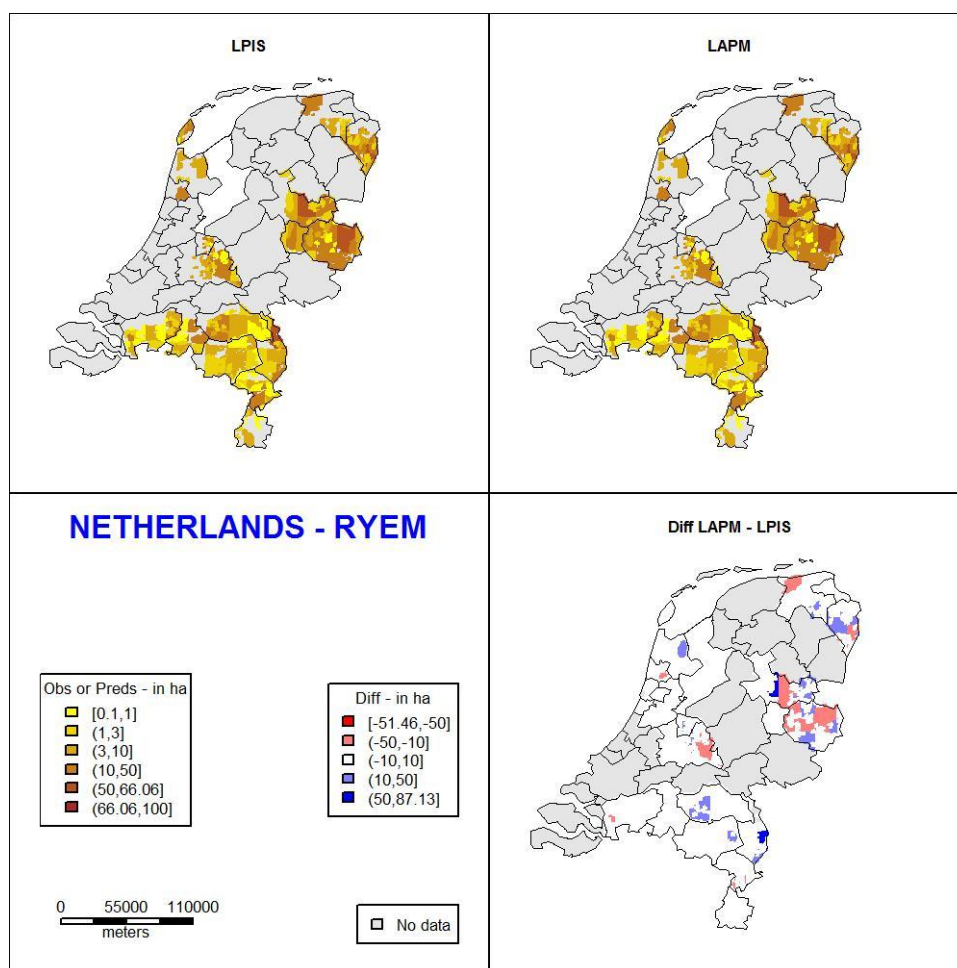


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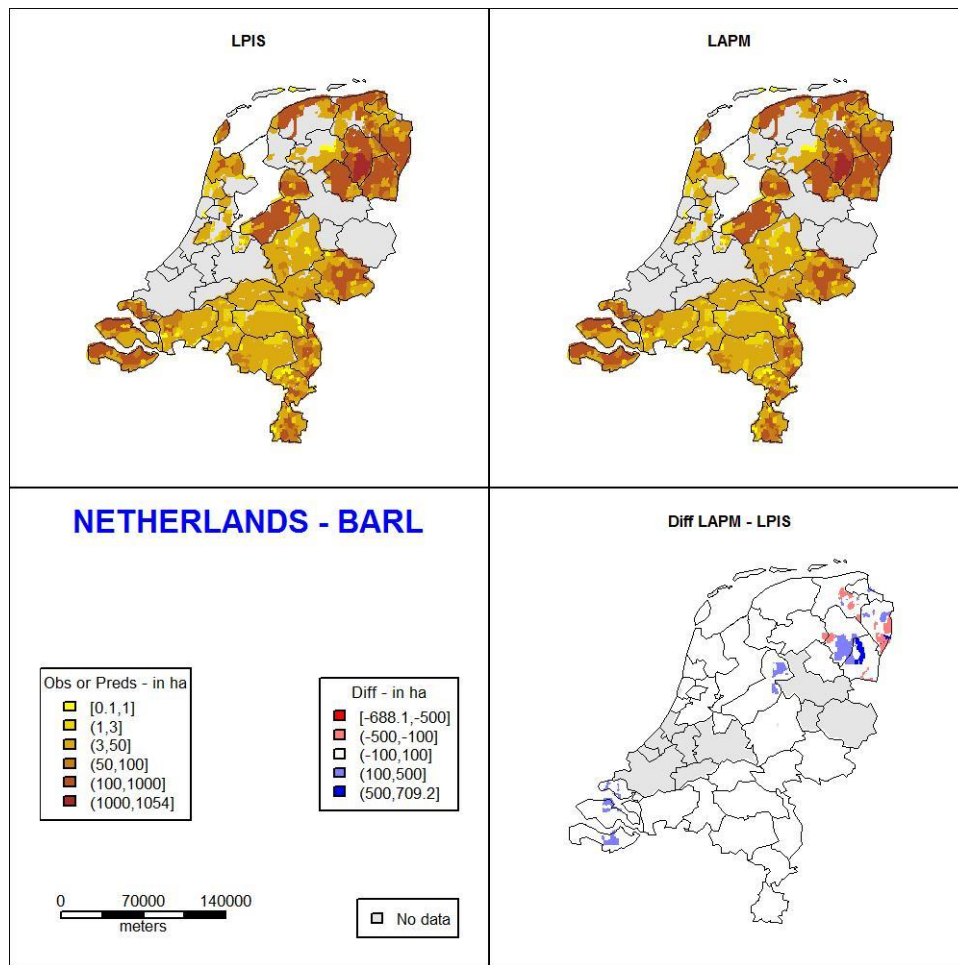
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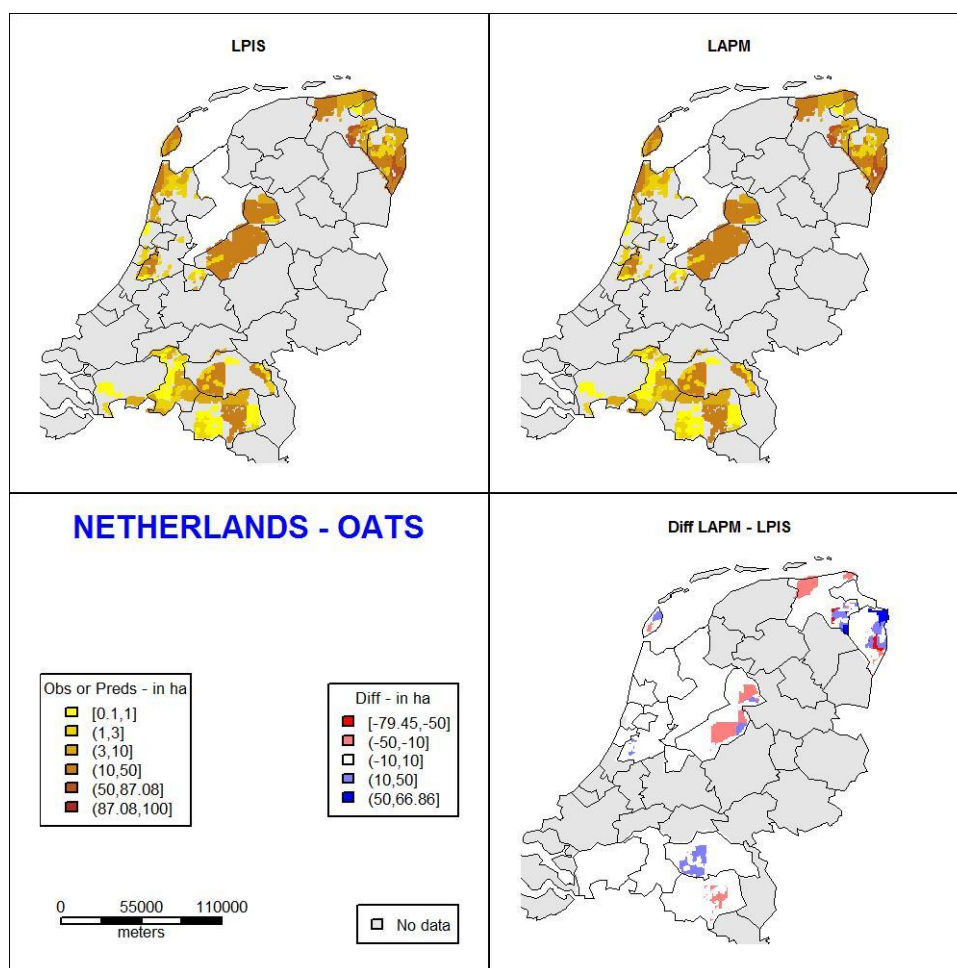
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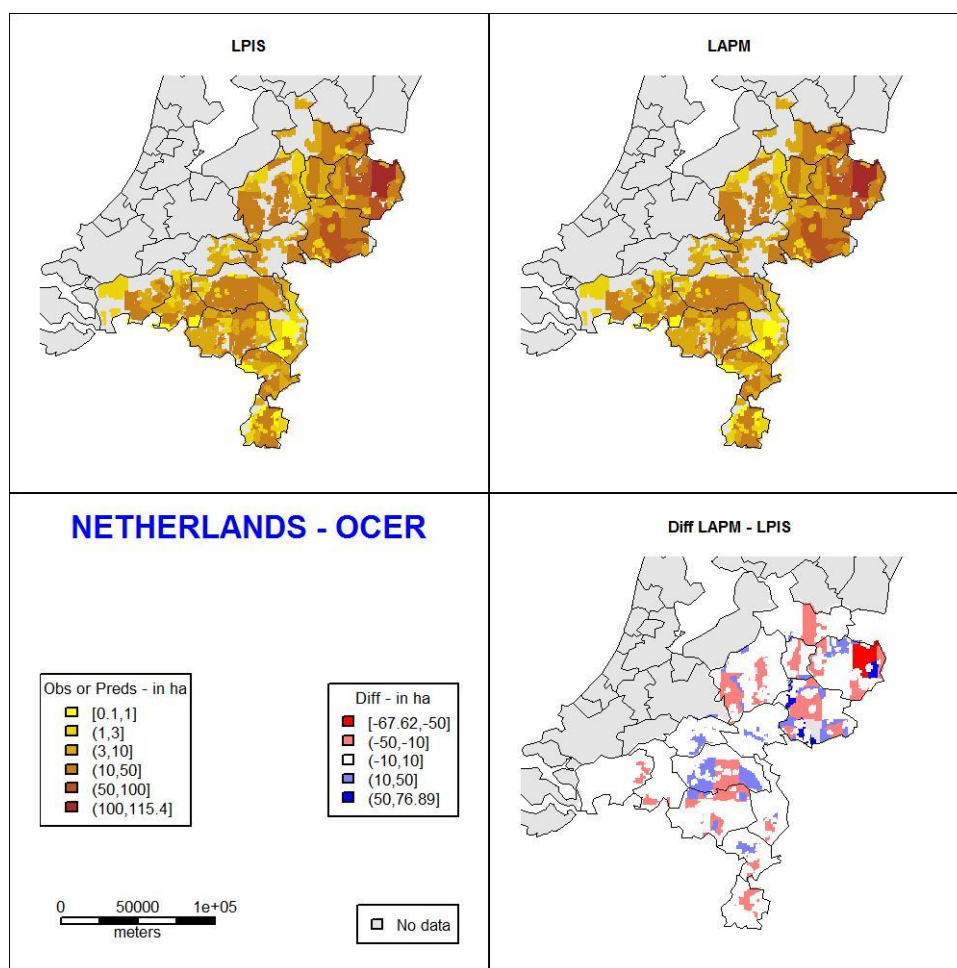
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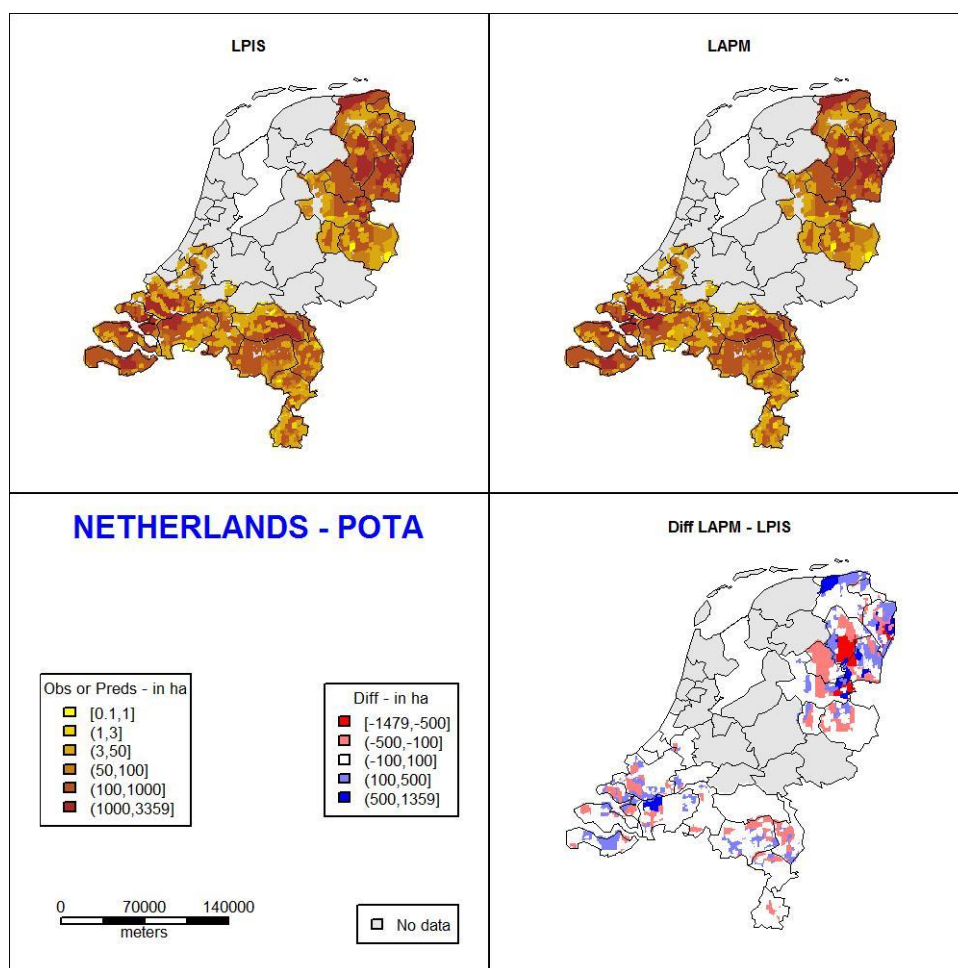
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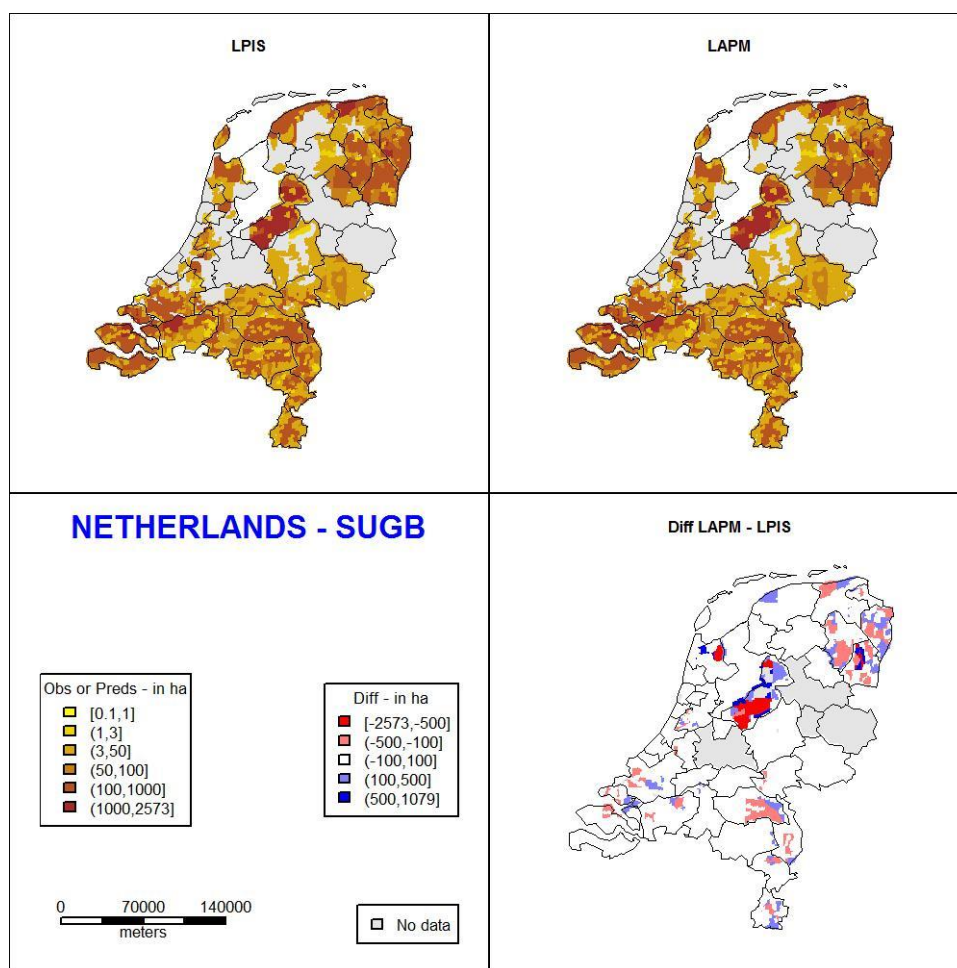
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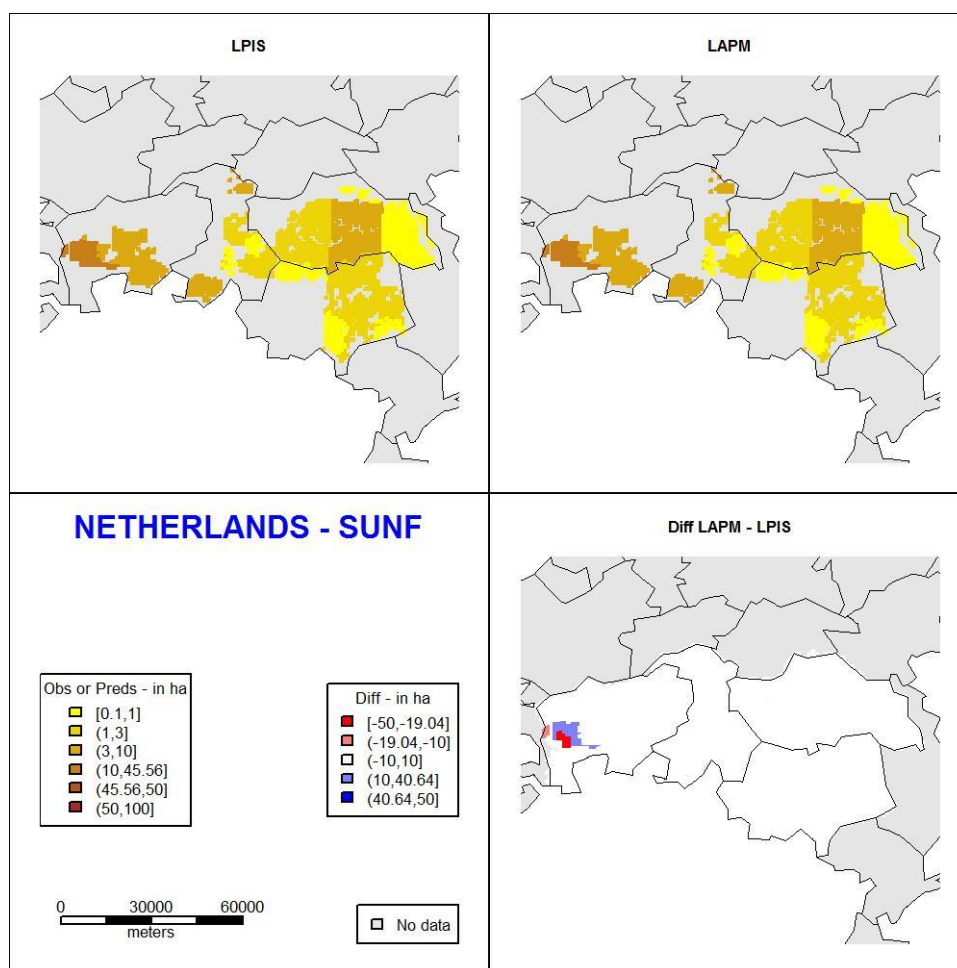
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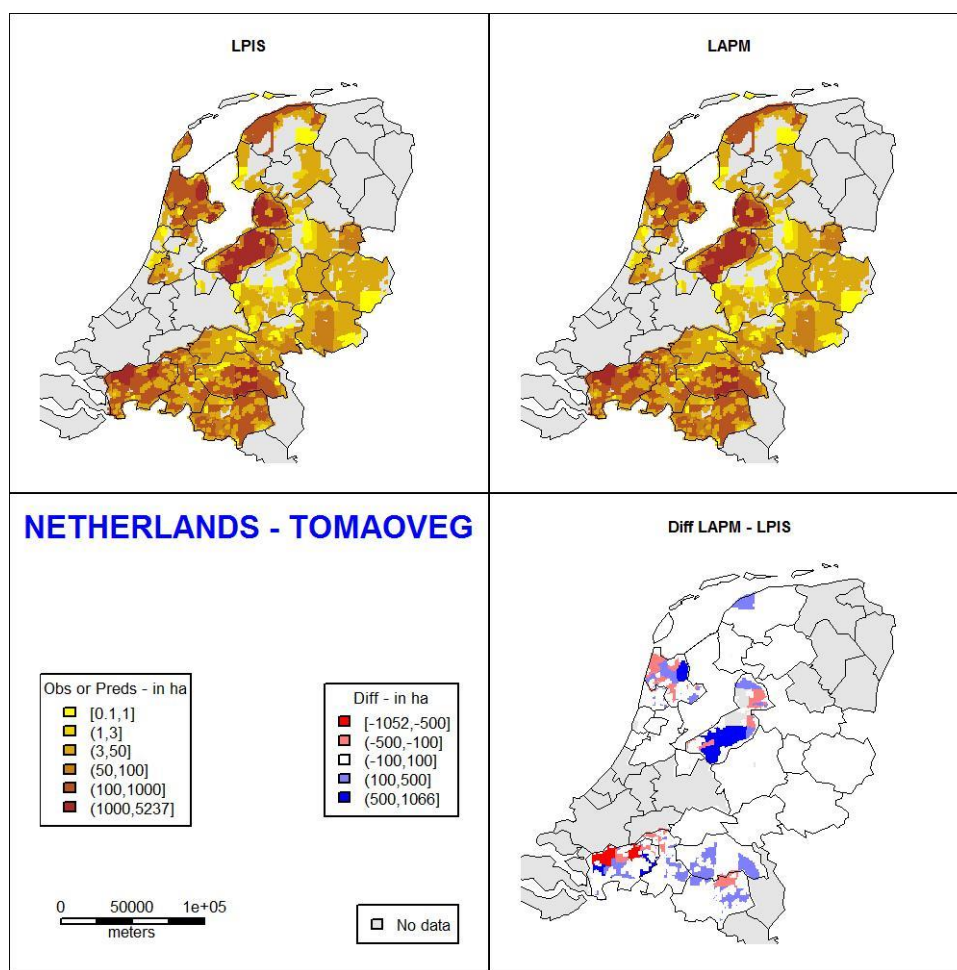
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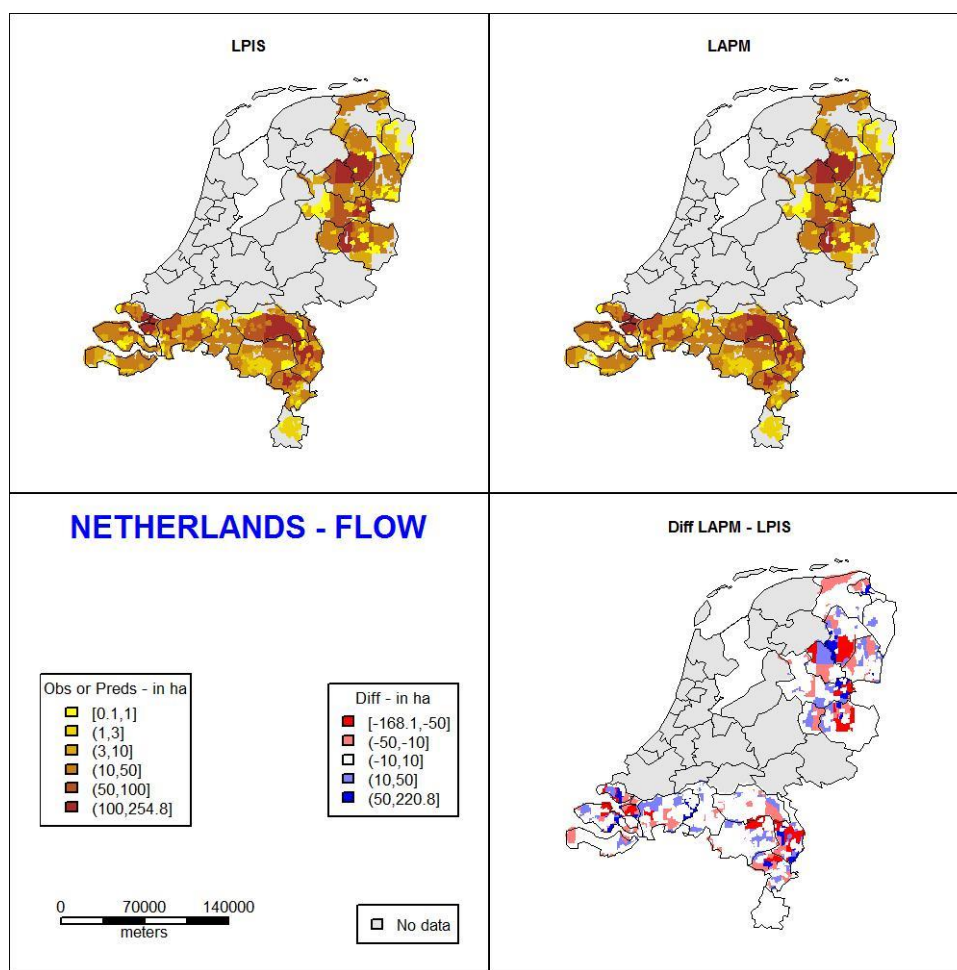
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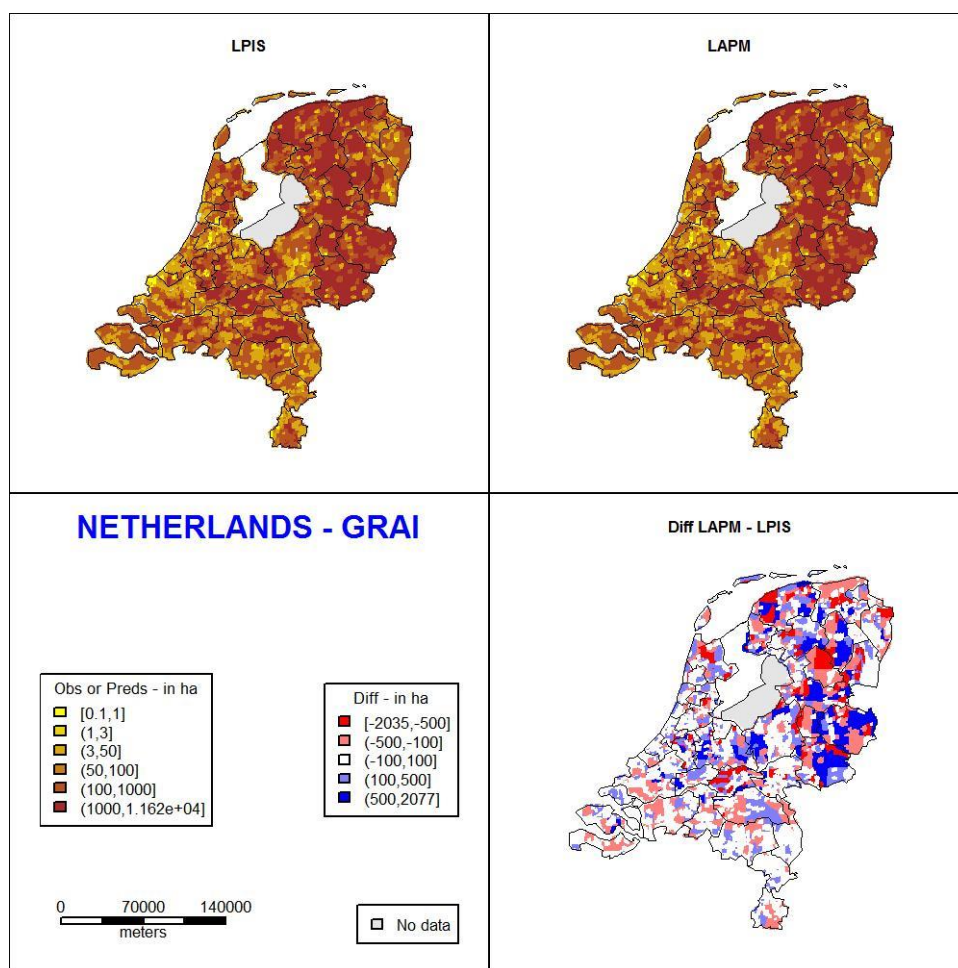
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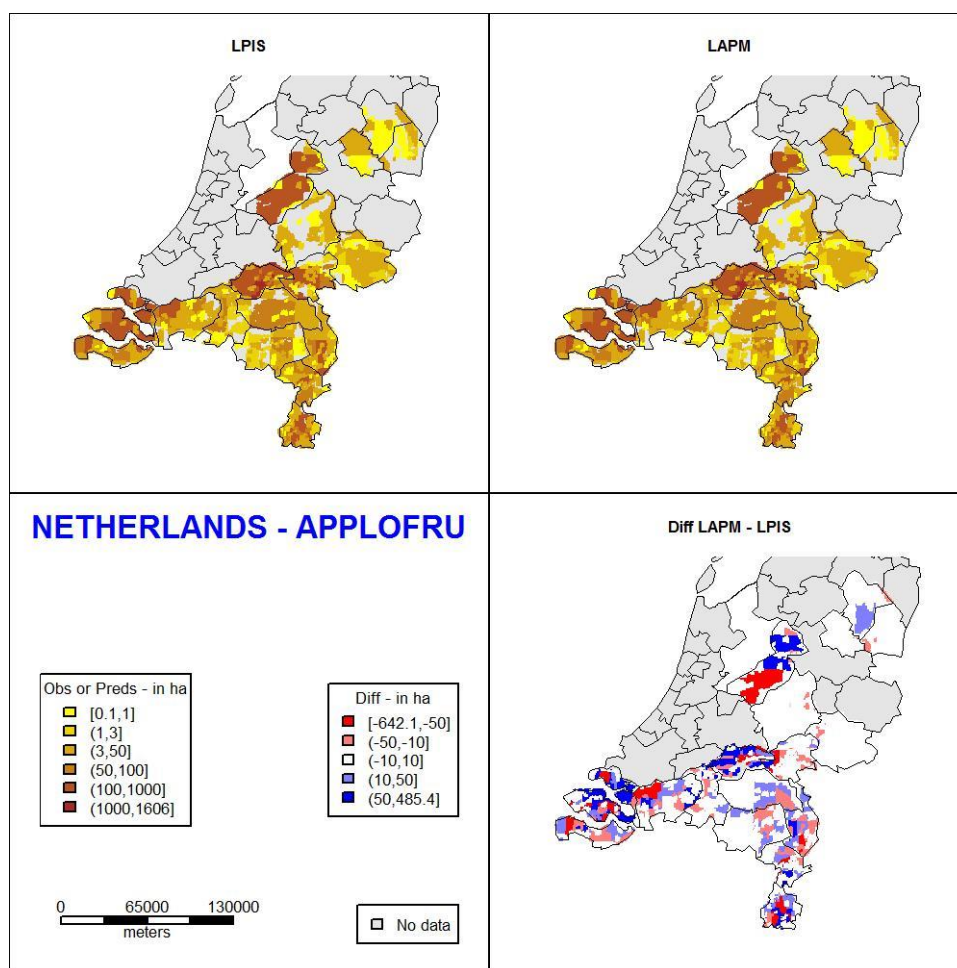
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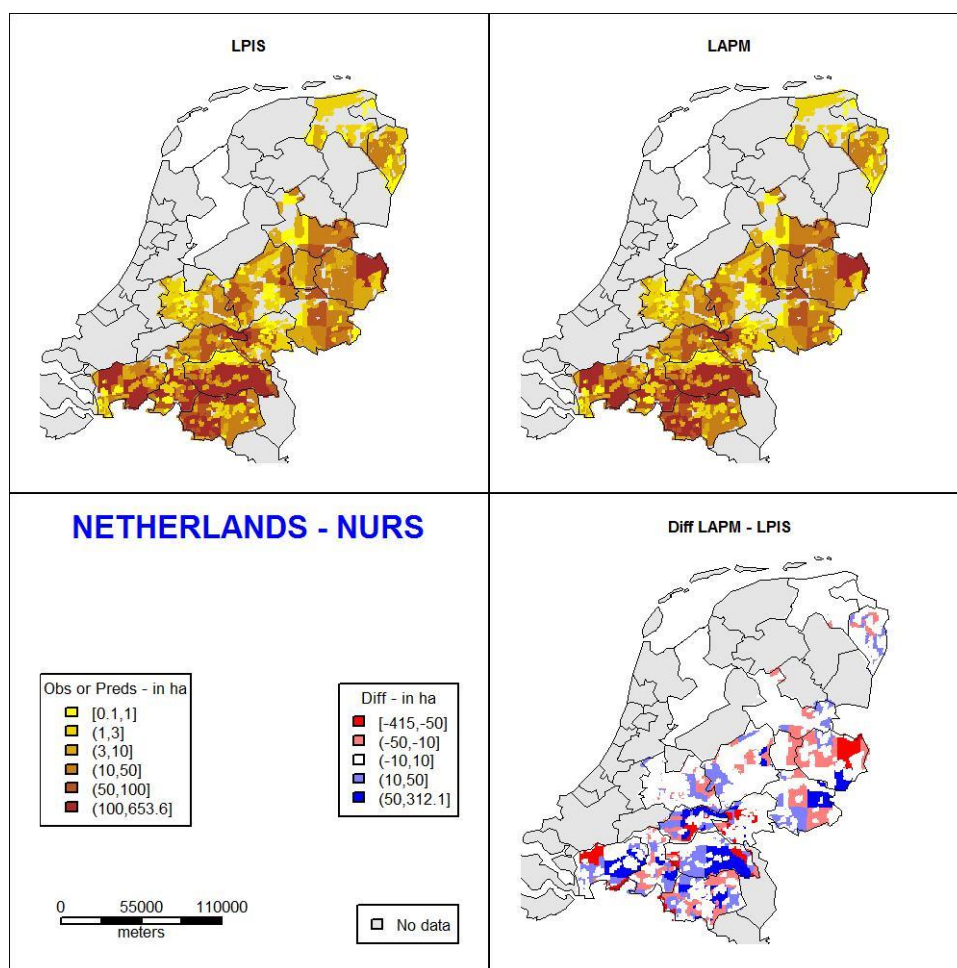
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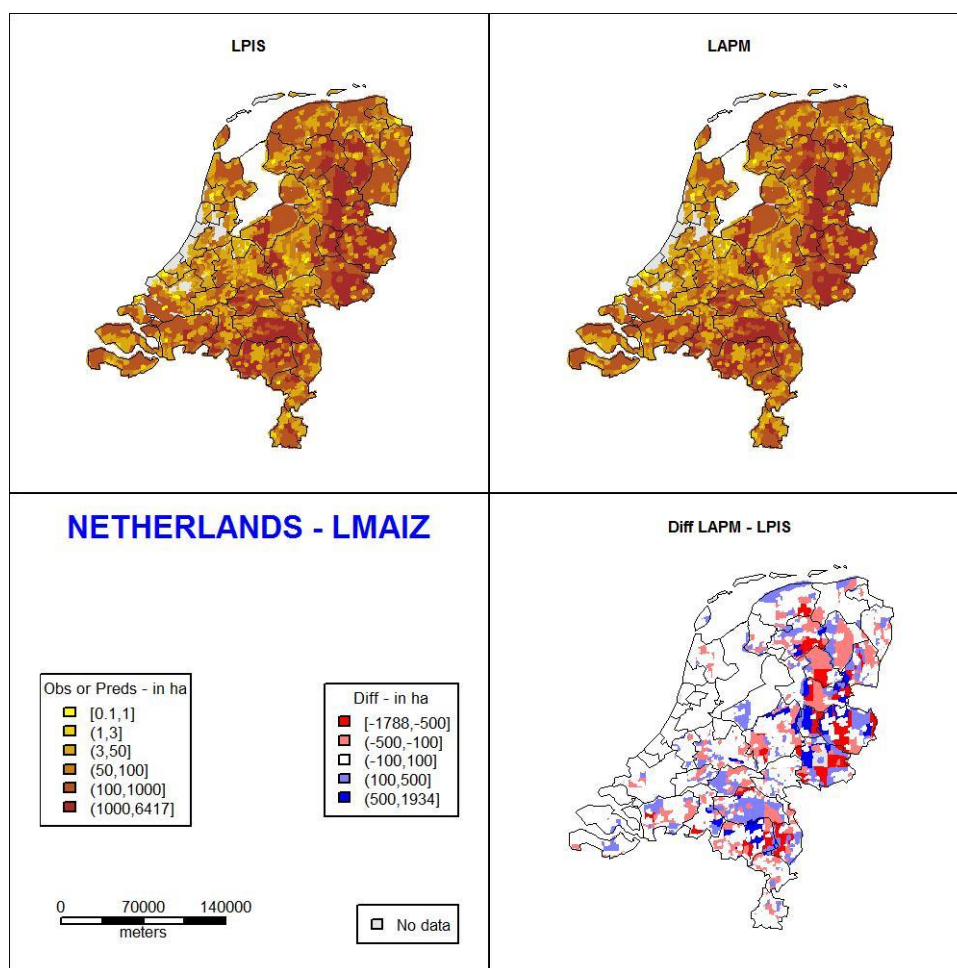
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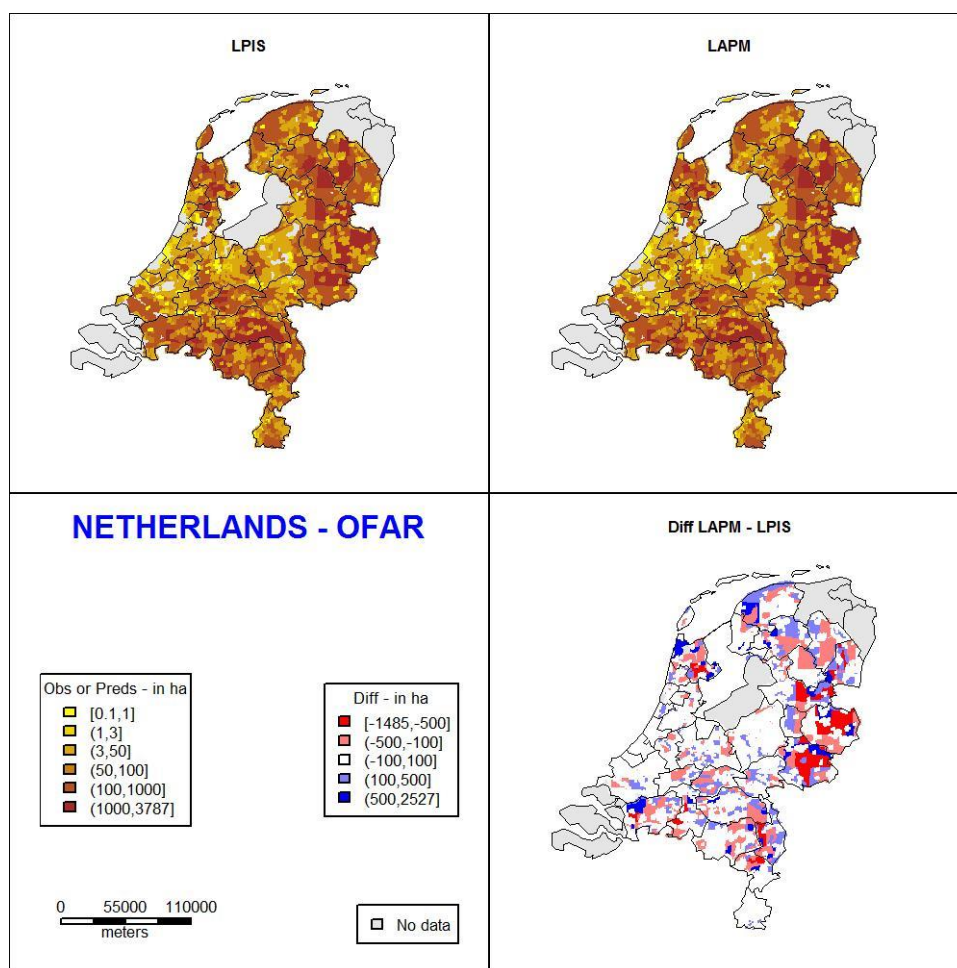
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